The September Effect:

An analysis of 11 stock markets

Jorge Gabriel Carvalho Aranha Ayres Pereira

up201507233@fep.up.pt

Dissertation

Master's in Finance

Supervisor:

Júlio Fernando Seara Sequeira da Mota Lobão, Ph.D.

April 2nd, 2018

Bibliographic Note

Jorge Gabriel Carvalho Aranha Ayres Pereira was born on 20^{th} July 1987, in Macau. Bachelor’s degree in economics at the Universidade de Aveiro in 2014, post-graduation in Finance and Taxes at Porto Business School in 2015. Concluded the theoretical part of the course in 2016 of the master’s in finance at Faculdade de economia do Porto.

Abstract

The September effect can be described by a result of average negative returns in September and is considered the worst month of the year Siegel (2014). There are some different hypotheses to explain this seasonal event. For example, the arrival of winter causing negative returns due to a depressing effect on the lack of daylight, families who need to sell stocks to pay for vacations, school, economic conditions or the beginning of the tax-loss effect. This thesis presents empirical evidence related to the September effect in some indexes, which challenges the theory of market efficiency hypothesis. It was studied eleven national indexes and considered two models for the study the OLS with the HAC estimator and the GARCH(1,1). The empirical results show that it is required more research to have better conclusions about the September effect. The OLS model with the HAC estimator was not good enough as it failed in all markets in the F-Test. The GARCH (1,1) model was found significant returns in certain periods as 2005-2016 for the indexes S&P500, DEUTSCHE BORSE DAX, FTSE 100 HONG KONG, NASDAQ and FTSE/JSESA ALL SHARE, in the years of 1987-2016 for the index FTSE 100 HONG KONG. The OLS with HAC estimator model does not provide any guidance to investors take advantage to obtain abnormal returns. The GARCH (1,1) seems to provide some guidance to investors in terms of obtaining abnormal returns in some markets in certain periods.

Key-words: seasonal anomalies, September effect, anomalies, market efficiency.

JEL-Codes: G11, G14

Resumo

O efeito de Setembro pode ser descrito pelo resultado médio de retornos negativos no mês de Setembro e é considerado o pior mês do ano. Existem diferentes hipóteses para explicar este evento sazonal. Por exemplo, a chegada do inverno causando um efeito de retornos negativos devido a um efeito depressivo provocado pela falta de luz solar, famílias que precisão de vender acções para pagamento de férias e a educação, condições económicas ou até o inicio do *tax-loss effect*. Esta tese apresenta evidencia empírica relativamente ao efeito de Setembro em alguns mercados, desafiando a teoria da eficiência de mercado. Foram estudados onze índices nacionais e considerados dois modelos para o estudo o OLS com o estimador HAC e o GARCH (1,1). Os resultados empíricos mostram que é necessária uma melhor investigação para retirar conclusões acerca do efeito Setembro. O modelo OLS com o estimador HAC demonstra não ser suficiente, pois falhou em todos os mercados no teste-F. O modelo GARCH (1,1) foi encontrado retornos significativos em determinados períodos como 2005-2016 para os índices S & P500, DEUTSCHE BORSE DAX, FTSE 100 HONG KONG, NASDAQ e FTSE/JSESA ALL SHARE, nos anos de 1987 a 2016 para o índice FTSE 100 HONG KONG. O OLS com o estimador HAC não permite obter qualquer orientação de investimento para retirar partido de retornos supranormais. O GARCH (1,1) parece fornecer alguma orientação aos investidores na obtenção de retornos supranormais em alguns mercados em certos períodos.

Key-words: seasonal anomalies, September effect, anomalies, market efficiency.

JEL-Codes: G11, G14

Acknowledgement

For the present work of investigation, it deserved a group of contributions, resulting in clear benefits which I would like to show my sincere gratitude in public. I want to thank all the support given by my supervisor PhD Professor Júlio Lobão for all efforts to develop this thesis. I want to express my gratitude to the PhD Maria Eduarda Silva for being available on such short notice before I left Portugal to work in Denmark. I would like to give special thanks to my family, Filipa’s family and Filipa Figueiredo who supported me during the development stages and for all the patience and understanding for the lack of attention while I was working on this project. I would like to thank my friend Luis Osswald for the friendship and support given during my Masters and personal life. A very special thank you to Mario Cardoso for all the patience and help during the masters and friendship. I would also like to express my gratitude to the companies RHmais Sa, Moldiflex Lda. and Nestlé Danmark for the extra time given to let me finish my studies.

Contents

Table Index

1. Introduction

Financial markets have been studied to be better understood on how they operate. The most accepted theory to date by academics is the efficient market hypothesis, whereas its base includes the random walk theory and that price reflect all information. The efficiency market hypothesis started with Roberts (1967), with the introduction of the term random walk and later was proved by Fama (1970) that market prices reflect private and public information and developed the efficient market hypothesis.

Since the introduction of the efficiency market hypothesis, there has been a development of empirical studies about stock returns by the day of the week and by the month of the year and anomalies were found. These anomalies challenge the market efficiency hypothesis as the theory includes the random walk theory. The random walk theory describes that it is not possible to predict the future returns of the securities. Calendar anomalies have intrigued the academics for decades, and it became essential to understand the motives that lead to its existence. The most studied calendar anomaly to date is the January effect.

The topic of this dissertation is about the September Effect. The September effect is represented by a negative average monthly return for over 100 years in the financial markets (Siegel, 2014). What makes it an attractive topic to explore is that this anomaly goes against the efficiency market hypothesis and, also, there is a lack of literature on the subject. The goal of this dissertation is to answer the following research questions: "Does the September Effect still exists?"; "Is it possible to profit from the September effect?". The knowledge obtained through this kind of research will help investors to understand the market better, and as a result, the market may correct itself. Also, it is relevant for science as it questions one of the fundamental assumptions that created the Market Efficiency hypothesis, namely is the Random Walk theory.

This thesis structure is as follows. The literature review will be provided in chapter 2 and divided into the following topics: Market Efficiency, Calendar Anomalies and the September Effect. The chapter has the purpose of making a theoretical introduction to the market efficiency theory and seasonal anomalies theories. At the end of this chapter is done a critical analysis of the literature.

The chapter 3, the data and methodology, is divided into the Data and Methodology.

The methodology provides a theoretical background on what academics found as best for these type of studies, and the steps of its application.

The chapter 4 contains the analysis and discussion of the results.

The last chapter 5 provides the conclusions and limitation of this study, as also some suggestions about future studies.

2. Literature Review

In this literature review, it will begin with the basics of the theory of Market Efficiency hypothesis and how it developed until the market anomalies. The goal of this chapter is to understand the basics which formed the Market Efficiency hypothesis. On the chapter about seasonal anomalies, it will cover some of the authors who identified the anomalies and their explanations for each of the event (Day of the week effect, January effect, September Effect).

2.1 Market Efficient Hypothesis

There have been an extensive about Market Efficiency in the Financial Markets. The main studies that cover this topic were initiated by Roberts (1967) and later discussed by Fama (1970). Market Efficiency hypothesis describes that the market prices reflect the available information. The Market Efficiency hypothesis was developed by numerous authors and consolidated the theory with Roberts (1967) and Fama (1970).

Fama (1970) defines Market Efficiency Hypothesis. As a base of the hypothesis, Fama (1970) describes that it is not possible to beat the market consistently as the market is not predictable since it follows a random walk. The Market Efficiency Hypothesis is also described by the reflection of prices on three levels: Strong form, Semi-Strong Form and Weak form. The hypothesis of Weak form is that prices fully reflect information based on historical prices, meaning that is a weak form of the efficiency. The Semi-Strong form is when prices reflect all public information. The Strong form when prices reflect all public and private information.

Additionally, Fama (1970) described the Joint hypothesis problem when testing the Market Efficiency Hypothesis. In case the market is found inefficient or the asset pricing model used to test the efficiency is not correct, becoming impossible to verify the Market Efficiency.

2.2 Seasonal Calendar Anomalies in the Stock Market

The theory of the market efficiency hypothesis states, as the base of the theory, that the markets reflect private and public information and it is not possible to predict the future price. Challenging this theory there are the seasonal calendar anomalies where it is put into question the randomness, there is some evidence of average significant returns during a specified period of the day of the week and month of the year. It became interesting to academics understand better how financial markets behaviour and results. This chapter covers different seasonal anomalies studies from different authors.

2.2.1 Day of the week effect

This anomaly is described by a higher or lower daily return in certain days of the week when compared to the remaining days. French (1980) found that Monday returns have a negative daily return average, while returns between Wednesday and Friday have a positive daily return average. To explain the day of the week Rystrom & Benson (1989) suggested that it is influenced by moods and emotions which might lead to irrational decisions. The author suggests that Friday after moons might influence in more purchases, and on Monday mornings since it is affected by a less positive mood could increase the level of sell orders. After these papers there were several empirical studies done by different authors to compare different market behaviours to find the anomaly, until today.

Barone (1990) studied the Milan Stock Exchange, the period of 2nd January 1975 until 2nd August 1989, for anomalies such as weekend effect and public holidays. The results obtained were in line with the US Market. The author considered that one possible reason for the weekend and holiday effect is that bad news related to stocks usually come on weekends or when the stock exchange is closed.

Siegel (2014) describes in his book that the Monday effect is considered the worst day of the week for the market for over the past 112 years. If the market were only through Tuesday through Friday, the Dow Industrial Average would be nearly double its current level. Friday is considered the best day of the week. The Monday effect is not confirmed in

U.S. Equity markets, but throughout the world, Monday is regarded as a poor day. On the major countries Wednesday, Thursday and Friday are positive average returns. The author also describes that Tuesday is also a poor day and that was found the poor Monday in the United States influences Asian market on the next day.

Gregoriou et al. (2004) study the UK stock market for the period of 1st January of 1986 to 31st December 1997 for the day of the week effect while using a GARCH (1,1) model. The conclusions taken on this study was that the week effect exists in the UK stock market and if the transactions costs have been accounted for, the day of the week seems to no longer have a statistically significant effect. Mondays were found as the higher standard deviation compared to the other days of the week, as Mondays as it was the day of the week anomaly.

Mazumder et al. (2008) studied the iShares for 17 countries and Standard and Poor's Depository Receipts (SPDRs) with the purpose of finding the day of the week effect and understand how it is possible to capitalise from it. The period of this study was from 7th February 2000 until 31st December 2003. The authors found evidence that a dynamic strategy while using the day of the week effect produces a higher return when compared to a buy and hold strategy, being the entry point near the close on Monday and the exit point on Friday.

Zhang et al. (2017) used the GARCH (1,1) model to investigate the day of the week effect in 28 markets from 25 countries. The primary goal of the authors was to examine the day of the week effect 15 indices from 13 emerging markets and 13 indices from 12 developed countries. The sample period is different from market to market, and it was created samples starting in the year of 01/01/1990 until 06/07/2016 while using the Rolling sample method. The authors concluded that day of the week effect exists on all 25 markets.

It can be concluded that the Monday is considered the worst weekday for trading and that between Wednesday and Friday is considered the bullish days as it is found the average return. With the transaction costs included the weekday effect end up to have no effect in the returns. Still it is relevant to study further to understand better the behaviour of the market as the information available is not enough to account the motive for its existence.

2.2.2 January Effect

According to Siegel (2014) the January Effect is considered the most important calendar anomaly. This effect is described by the highest average monthly return over the year. The average return on the S&P500 Index from 1925 until 1997 was 1.6 percent, while the average of small stocks was 6.2 percent. The author states that January effect prevailed the most powerful bear market (1929). A strategy suggested by the author is buying at the end of December small stocks and selling at the end of the month of January.

There are studies where the authors suggest that the presence of this effect is due to tax reasons (Roll, 1983) because small firm stocks are more affected by the tax-loss selling than the large firm stocks are according to Reinganum (1983). Gultekin & Gultekin (1983) describe that there is a presence of seasonality in the major industrialised countries, where in most cases is after the turn tax year with the presence of high return.

Haug & Hirschey (2006) used as data the period of 1802-1926 data from Schwert (1990) and Center for Research on Stock Prices (CRSP) value-weighted portfolio returns from 1927-2004. The goal of this study was to update the evidence on the January effect in value-weighted returns for large-cap stocks 1802-2004 and equally weighted returns for small-cap stocks from 1927-2004. The authors found a significant January effect for small-cap stocks, even after the Tax Reform Act of 1986. The authors believe the continuous presence of January effect still is statistically significant since 1987, weakens the argument of the tax effect as an explanation for this event.

Chou et al. (2011) with the purpose to investigate the seasonal effect in value premium puzzle, it studies the book-to-market effect as an outcome of the January effect. To do this study the authors considered portfolios based on size and the ratio of book value of equity

(BE) and market value of equity (ME) as suggested by Fama and French to define value premium and investigate the seasonality of the BE/ME effect. This investigation led to evidence that supported the value premium has different patterns in January and non-January months for large and small capitalisation firms. In the month of January, it was exclusively found a significant value premium. This high premium is led by the losers' stocks at the turn of the year. For this study, it was used data from the Center for research in security Prices (CRSP) and merged Compustat annual industrial files of the income statement and balance-sheet data from the period of 1926 – 2004 and it was used to analyse NYSE, Amex and Nasdaq.

Shelby & Frank (2014) study involved an analysis of 90 companies, where it was selected randomly 30 companies for each year 2010, 2011 and 2012. The data collected from yahoo finance page from the stock return of each equity and the S&P500 index. It was tested the effect of the year and selling underperforming stocks on the stock price. To do that it was analysed the last 30 days returns before and after the last trading day of the year for each year, where the authors believe that it would allow understanding the benefits of trading in the month of January. The conclusion taken in this study was that the market is efficient concerning the January effect and support the weak form of market efficiency.

The January effect is found significant in most of the studies available about seasonal anomalies, with the application of different models. The most widely accepted hypothesis for the existence of the January effect is the tax effect. The paper from Haug & Hirschey (2006) challenges the tax effect as an explanation, which means that with the current information available by academics might not be enough to explain the January effect presence.

2.2.3 Other Effects

Agrawal & Tandon (1994) paper studied eighteen countries for effects found by different authors. The analysed effects were the weekend effect, end of December effect, turn of the month effect, monthly effect and Friday the thirteenth effect. This study found mixed evidence related to the weekend effect between the countries. Monday returns are the lowest and negative in nine of the countries, while eight other countries the lowest returns are on Tuesdays. These results are not entirely consistent with the US market. The Friday effect was not significant and positive only in Luxembourg market, while the other markets had positive and statistically significant returns. Related to the turn of the month effect it was found significant in fourteen countries, where it was observed statistically significant positive returns over the four days around the turn of the month and the last trading day. The end of December pre-holiday returns was found positive and significant in eleven countries, and during intern holidays period, it was found positive and significant in fourteen. The Friday the thirteenth effect according to the author was not found significant in any stock markets examined.

Kamstra et al. (2000) describe in their study that there is a significant negative return on financial market indices on weekends from daylight savings. The argument for the presence of this anomaly is the result of sleeping patterns as the effect found (roughly 200 to 500 percent of the regular stock returns on Mondays).

Bouman & Jacobsen (2002) found that basing the trading strategy on the term “Sell in May and go away” can generate abnormal returns in most indexes of the world. The authors confirm that August and September are considered as bad months. The strategy implies to sell in May and buy at the end of September or beginning of October.

Heston & Sadka (2006) study shows that stocks tend to have high or low returns each year in the same month at yearly intervals up to 20 years. A strategy based on historical prices of the same month shows that a long or short-term trading strategy will lead to excess returns.

2.3 The September effect

The month of September is a very curious month since there is a lack of studies, the media and some authors define it as the worst month of the year in the US market. It is curious to understand until which point this affects other markets in the world and if it persists.

Siegel (2014), the September effect lasts in the US market for more than 100 years. From data gathered by Siegel (2014), a value-weighted stock index with dividends included between the years of 1885-2006, the month of September represents a negative average return and is considered to be the worst month of the year in the US market. This effect is also present in other markets in the world. Different researchers try to explain a reason why the September effect exists. Siegel (2014) describes various hypothesis such as the possibility of investors selling stocks to pay vacations or holding off to buy new stocks. The month is equivalent to the Monday effect since it is considered as a month with the most average negative returns. The other possibility discussed by the author is the beginning of autumn since there is evidence that the presence of sunny days will affect the well-being.

Gibson et al. (2000) researched about the year of 1986 after the Tax Reform Act replaced non-synchronous tax year-ends with a common October 31st year-end for all mutual funds. They discovered that around 30 percent of equity funds was generated in December fiscal year-ends and the rest of equity funds occurred in fiscal year-ends distributed in the other months during the year. Many funds changed the fiscal year-end to October 31st after the Tax Revision Act, and around 21 percent of funds came out of October fiscal year-ends in 1996. The authors describe a November effect on the year of the Tax Revision Act, but during the following years the prices change are not significant in a certain month of the year. The authors found a pattern of momentum trading by mutual funds after the passage of TRA where there is a systematic seasonal component corresponding to the funds' tax year-end. Also, the authors did not find statistically or economically significant benchmark-adjusted returns consistent with a November effect, where it was searched for a similar event to a January effect. Interestingly the authors found on the year of the TRA a rebound-on price after a negative return on October in the month of November, being consistent with price pressure as fund managers have some incentives to realising capital losses before 31st October. This study also found that mutual fund managers spread the sale of the losers over relatively long-time horizons heading into their tax. This study is relevant as it provides an opportunity to examine the tax laws influence on a certain month and understand if it influences over the month of September.

Hirshleifer & Shumway (2003) investigated the relationship between the daily returns in New York Stock Exchange with days with sunny or cloudy conditions. They found that stock returns are significantly higher on sunny days than on cloudy days, suggesting that investors emotional state influences stock prices. It would indicate that the September effect could be related to the beginning of the winter season.

Kamstra et al. (2003) concluded that seasonally depressed investors become risk averse at the start of the autumn, resulting in a poor performance of the financial market. They found evidence showing that there is an inverse relationship between security preference between riskier and safer securities during the year (ex: the relationship between stocks and bonds). They have concluded that as stock returns tend to drop during autumn and the bonds, returns tend to rise. They also found that during autumn where stocks tend to drop, they found evidence that there is a preference for investors on holding safer portfolios. It is the evidence where there is an aversion to holding risky securities and an increased preference for holding securities with fewer risks. In their research, they also found that mutual funds' money, during the fall and winter, moves from stocks into bonds. Kamstra, Kramer, Levi (2003) also concluded that September is, on average daily returns, at the lowest point of the year in the US Market where it recovers during fall and on December it becomes positive with a peak in January. The raw data suggests that September and January may be the extreme points on a seasonal cycle. For the authors to be sure that the reaction in the world was, all the same, they shifted the results of the data for six months to be aligned with the season of the year between countries, where fall begins for Northern Hemisphere countries in September and in March for the South Hemisphere countries.

They have concluded that the equivalent month of the beginning of the fall (September) was the lowest peak point and January was the highest peak point.

Kramer & Weber (2011) based on the previous studies, these authors realised a practical exercise which consisted of giving people 20$ and options to invest. They realised that the investors who suffer from Seasonal Affective disorder tend to be more sensible to the market, and therefore they are more influenced by the negative environment. Still, the study does not guarantee that this is true. One of the research conclusions was that there was a similar reaction (while ignoring the higher impact) to changing the securities along the year from safer securities to riskier ones. The authors could not determine who was reacting most uncharacteristically, but they thought that seasonal affective disorder and non-seasonal affective disorder participants might have responded differently to the crisis conditions in the financial world. Although the research conclusions were in line with the hypothesis, the authors could not confirm that this is enough to explain the market reactions.

Gu & Simon (2007) found that September return of the indices is negatively related to interest rate and positively related to GDP growth, inflation rate, and market stock performance of the year. They also pointed out that the tax-loss selling, and macroeconomic seasonality could contribute to September's poor performance. The author concluded that the fourth and fifth week when the Monday effect occurs contributed the most to the September effect's poor performance. The markets in the study were the Dow Jones index for the period of 1896 – 2005, the S&P 500 for the period 1950 - 2005 and Nasdaq for the period 1971 – 2005.

Haug & Hirschey (2011) reviewed the September effect and considered that it could not be easily dismissed as a reflection of institutional consideration, time-period considerations, and differences in return measurement criteria. The author considered using the data from the paper Schwert(1990) (the author considered data from the S&P500) and Center for Research on Stock Prices (CRSP). While September returns are positive 56.4% of the time, September is the only month in which a negative average return -0.26% is observed for the value-weighted portfolio over the sample period of 1802-2006. The author found that there is an accumulative return of September -53% from 1802-2006. The negative return appears to be concentrated in both large and small value stocks. The authors also reviewed some behavioural motives such as the influence of the mood of the investor based on sunlight conditions and also how affected is the results of the returns of investors who suffer from seasonal affective disorder (Kamstra et al., 2003).

2.4 Critical analysis of the literature

Since 1827 there have been significant contributions until the Market Efficiency hypothesis. I consider that Bachelier's (1900) work was the key to the development of the theory, as he was able to develop the mathematical model where other authors could work. Later, Fama (1970) was able to consolidate all the knowledge and revolutionise the literature with the Market Efficiency hypothesis. Still, we can understand that there is some incompleteness to explain market behaviour since there are seasonal anomalies present in the market. With the studies of market anomalies, we can have an idea of the different possible explanations for their presence.

On the topic of this dissertation, the September Effect, there is a lack of studies in the literature regarding September Effect in the financial markets. Siegel (2014) quotes the hypothesis of being the reason to pay vacations and to pay school. Even though the hypothesis is reasonable to explain the motivation of a negative presence during September, there is not yet any study capable of supporting and proving this hypothesis.

Gibson et al. (2000) study is important to highlight that the Tax Revision Act did not influence the September effect, but affected the month of November. It is my opinion that this fundamental aspect opens an essential topic over the September Effect as it reinforces that tax reason creates a selling pressure before the new tax cycle and has not affected the month of September.

Considering Hirshleifer & Shumway (2003) study of the investor behaviour, it is not enough to explain why the financial markets pricing will be based on the mood of the investors. Although this study has some limitations as it only covered the cloudiness in New York city and also it is not considered a good proxy to explain the mood of the market. There are other countries such as Australia where September effect is present, but the month of September represents the beginning of spring. The authors Kamstra, Kramer, Levi (2003) and the continuation study Kramer & Weber (2011) opened an important discussion about market preference on securities during the year, the investor which suffer from seasonal affective disorder security preference during the year and also about non-seasonal affective disorder. These studies give some hints that the reaction to prices is enhanced by the mood of the investor that will have an impact on financial markets. They also identified mutual funds, changing their preference during the year. The reason for that is unknown but could be related to emotional state or could be profit taking or tax reasons on securities with bad performance in the market. Still, this helps us understand why there is a negative impact during this period with the beginning of September.

Gu & Simon (2007) enhanced the tax-loss selling hypothesis and the macroeconomic seasonality as two possible explanations that contribute to the September effect. The authors argue that current macroeconomic conditions contribute to the September's poor performance in the Financial market.

Haug & Hirschey (2011) investigated the month of September which empirically shows that September anomaly exists in all empirical studies (independently on the method applied). It confirms that the September effect is present in the US market.

It is interesting to understand the month of September based on other authors research. In my opinion, based on the research, the September month has several variables which makes this month the worst month of the year for already many years. The variables we can take into consideration are fundamental (ex: Payment of Vacation, School payments, economic environment), behavioural (ex: Sunlight, Cold) and historical (September is considered the worst month of the year for more than 100 years).

3. Data and methodology

3.1. Data

The data was collected from Thomson Reuters data stream over the years of 1964 until 2016 for several markets. All the information was gathered on 24th of March 2017. The type of data collected was the daily price index with dividends included. To be able to compare information for different markets, since the data is not available for all the years of the study for each market, it was created three groups of market indexes from various countries for the following dates: 1964-2016; 1987-2016; 2005-2016 were created:

1). 1964-2016: S&P500, NIKKEI225 and DOW JONES.

2). 1987-2016: S&P500, NIKKEI225, DOW JONES, MICEX, DEUTSCHE BORSE DAX, FTSE 100, FTSE 100 HONG KONG and NASDAQ.

3). 2005-2016: S&P500, NIKKEI225, DOW JONES, MICEX, DEUTSCHE BORSE DAX, FTSE 100, FTSE 100 HONG KONG, NASDAQ, EURONEXT LISBON. FTSE 100/JSESA ALL SHARE and NYSE.

List of Market Index

Table 1. List of the markets names, ticket codes and related country.

Ticket code	Index Name	Countries
GDAX	DEUTSCHE BORSE DAX	Germany
FTWIHKGL	FTSE 100 HONG KONG	Hong Kong
N225	NIKKEI225	Japan
PSI20	EURONEXT LISBON	Portugal
MCX	MICEX	Russia
FTJ203	FTSE /JSESA ALL SHARE	South Africa
FTSE	FTSE 100	United Kingdom
IXIC	NASDAQ	United States of America
SPX	S&P 500	United States of America
XAX	NYSE MKT	United States of America
DJ	DOW JONES	United States of America

For all indexes, the daily returns are calculated by

$$Rt \ = \ln\left(\frac{PI_{Trading\ day_t}}{PI_{Trading\ day_{t-1}}}\right), \tag{1}$$

where $PI_{Trading\ day_t}$, stands for the closing prices of an index at the time *t* and *t-1*, and where t is the day. The calculated results by Eq. (1) are a total of 3130 observations per index for the group of 2005-2016, a total of 7886 observations per index for the group of 1987-2016 and a total of 13827 observations per index for the group of 1964-2016.

3.2. Methodology

3.2.1. Literature review

According to French (1980), the calendar effect can be studied with the daily returns of the market index. In this paper, French (1980) studied two alternative models of the process generating stock returns, where it is considered the seasonal anomalies. In this study French used the following model to explain the expected return:

$$Rt = \ln(\frac{(P_t+D_t)}{(P_{t-1})}) + \mathcal{E}_t \ , \quad (2)$$

R_t is the expected return, P_t is the price at moment t, and D_t is dividend at moment t. It describes the behaviour of stock prices which can be described by a multiplicative random walk. It was used by the S&P500 to perform the study about the market anomalies. In this paper, French used a linear regression model (Ordinary Least Squares) to study the calendar effect, following other papers on the same topic.

Officer (1975) studied the possible economic implications of a seasonal effect in the Australian capital markets and the traps of using indexes. The author found challenging to detect seasonality in individual stocks after analysing the use of the market model to explain the expected returns on an individual stock. Officer (1975) concluded the seasonal effects should be more evident on portfolios of stocks and indexes.

When considering both papers Connolly (1989, 1991), it can highlight several limitations of the linear regression model on both papers. We may conclude while studying the market index returns they are likely to be autocorrelated, the residuals are non-normal and the variance o the residuals may not be constant.

While understanding the limitations of the OLS, Engle (1982) to correct the variability, suggested the use of autoregressive conditional heteroskedasticity (ARCH) as this model assume the variance of residuals is not constant over time and it is not possible to create a model to the error term. Since then, the ARCH model has been used to explain the conditional volatility in different types of financial series. This model was developed to study the inflation had its origin in the economic cycles, and this uncertainty would affect the behaviour of the investors. The ARCH process is described by:

$$a_t = \sigma_t \varepsilon_t, \tag{3}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_m \varepsilon_{t-m}^2, \tag{4}$$

Tsay (2010) explains that $\{\varepsilon_t\}$ is a sequence of independent and identically distributed random values with mean zero and variance 1, $\alpha_0 > 0$ for $i > 0$. The coefficient α_m must satisfy some conditions to ensure the unconditional variance is finite. ε_t usually follows a standard normal, student-t or generalised error distribution. The structure model $\{a^2_{t-i}\}^m_{i=1}$ implies a conditional variance σ^2 for the innovation a_t. The meaning of this is large shocks tend to be followed by another large shock and small shocks tend to be followed by low shocks. It is equivalent to a volatility clustering observed in asset returns. a_t is constant during time then a_t is white noise.

Later Bollerslev (1986) based on the ARCH model and created an extension known as the Generalized Conditional Heteroscedastic (GARCH) models, where the conditional variance depends not only on past volatility but also on past returns. Bollerslev (1987) suggests for time-series to use as the error distribution t-student. In a more general term, the GARCH model is defined by:

$$a_t = \sigma_t \varepsilon_t, \tag{5}$$

ε_t are random variables *iid* with a mean of zero and a variance equal to 1, independently on the past returns.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_s \varepsilon_{t-s}^2 + \beta_1 \varepsilon_{t-1}^2 + \cdots + \beta_r^2 \varepsilon_{t-r}^2 \tag{6}$$

The model is known as generalised autoregressive conditional heteroskedastic of the order (r,s) and is represented by GARCH(r,s). When r = 0 the model is the same as an ARCH(s) and the coefficients αi, (i = 1, … , s) and ϕj, (j = 1, … , r) are known as ARCH and GARCH coefficients. The following parameters of the model α_0, α_i and $\phi_{j,}$ when $\alpha 0 >$ 0, $\alpha i \geq 0$, (i =1, … , s) and $\phi j \geq 0$, (j = 1, … , r) are enough to guarantee $\sigma_t{}^2 > 0$. The condition max $(r,)$ $(\alpha i + \phi i) < 1$ i=1. Is enough to guarantee that conditional variance of σt is finite and σt is stationary.

Brooks & Burke (2003) mentioned the GARCH(1,1) model is enough to capture all the volatility clustering that is present in the data. Therefore no further lags are necessary and determination for the appropriate lag lengths. Further for the conditional variance equation, it is a difficult task to determine the correct lags. Therefore researchers use GARCH(1,1). The GARCH (1,1) takes the following form:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \varepsilon_{t-1}^2 \tag{7}$$

Newey & West (1987) developed an estimator to be used that attends to calculate the covariances. Tsay (2010) explains that it is commonly used for heteroskedasticity and autocorrelation models. The estimator is characterized by the following equation format:

$$\text{Cov}(\hat{\boldsymbol{\beta}})_{\text{HAC}} = \left[\sum_{t=1}^{T} \boldsymbol{x}_t \boldsymbol{x}_t'\right]^{-1} \hat{C}_{\text{HAC}} \left[\sum_{t=1}^{T} \boldsymbol{x}_t \boldsymbol{x}_t'\right]^{-1} \tag{8}$$

where

$$\hat{C}_{\text{HAC}} = \sum_{t=1}^{T} \hat{e}_t^2 \boldsymbol{x}_t \boldsymbol{x}_t' + \sum_{j=1}^{\ell} w_j \sum_{t=j+1}^{T} (\boldsymbol{x}_t \hat{e}_t \hat{e}_{t-j} \boldsymbol{x}_{t-j}' + \boldsymbol{x}_{t-j} \hat{e}_{t-j} \hat{e}_t \boldsymbol{x}_t'), \tag{9}$$

l is a truncation parameter, and wj is a weight function defined by:

$$w_j = 1 - \frac{j}{\ell + 1} \tag{10}$$

The author suggests choosing l to be integer part of $4(T/100)^{2/9}$.

Unit-root test

It is necessary to use a stationary time series data for financial time series modelling and analysis to non-stationary data because if time data is stationary as shocks may exist on time series and they gradually are eliminated. By using the Dickey & Fuller (1979) test, we will be able to understand if the daily returns of the index in study follows a random walk or a random drift.

H0: Stationary

H1: Not Stationary

3.2.2. Methodology applied

The methodology used consists in the usage of use two accepted models and compare the results between them. The first part was based on the study described in Bouges et al. (2009) where the author used the OLS model with the HAC estimator developed by Newey & West (1987) to examine the seasonal effect. The second part of the thesis was based on the paper Athambawa (2015) where the author used the GARCH (1,1) model to examine the seasonal effect. The use of this model will allow understanding whether the average daily return is significant. It is used the extended dummy variable, in this model, as this enables to analyse the monthly effect during the year.

The model used in this thesis for the OLS model takes the following form:

$$E(Rmonth) = c + \beta_2 * February + \beta_3 * March + \beta_4 * April + \beta_5 * May + \beta_6 * June + \beta_7 * July + \beta_8 * August + \beta_9 * September + \beta_{10} * October + \beta_{11} * November + \beta_{12} * December, \tag{11}$$

The E stands for expected average daily return, from β_2 to β_{12} represents the average daily return from February to December.

The second model used on the thesis with the GARCH (1,1) model will take the following form:

$$E(Rmonth) = \beta_1 * January + \beta_2 * February + \beta_3 * March + \beta_4 * April + \beta_5 * May + \beta_6 * June + \beta_7 * July + \beta_8 * August + \beta_9 * September + \beta_{10} * October + \beta_{11} * November + \beta_{12} * December, \quad (12)$$

The E represents the expected average daily return, from β_1 to β_{12} represents the average daily return from January to December.

As it is suggested by Tsay (2010), on the first step it is estimated an Ordinary Least Squares (OLS) model and test for Heteroskedasticity while using the ARCH-LM test and to test stationarity will be used the Augmented Dickey-Fuller unit-root test. These steps are necessary to understand if there is the presence of the ARCH effect and if the model is stationary. In case the ARCH test provides evidence in favor of the ARCH effect (which is expected to be) and the unit root test allows to conclude in favour of stationary (which is expected to be stationary). The next step it is to apply the OLS with the HAC estimator and the GARCH(1,1) with t-student as error distribution with the purpose to study the returns of September.

The first step consists on evaluating the data and the Ordinary Least Squares (OLS) model with the default estimator. After those tests are done it is expected to find the data stationary and with the presence of the ARCH effect. As finding these two tests positive, firstly it is used the Ordinary Least Squares (OLS) model with the HAC estimator (Newey & West (1987)) as described by Bouges et al. (2009) to test the data and search for evidence for the September effect with the extended dummy variables.

The null hypothesis of the test of the dummies is as defined:

$$H_0: \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = \beta_{12}$$

H_0 describes the expected returns for each month which have no significant impact as the expected return is equal to 0, if this hypothesis is rejected the returns have a significant impact. The goal will be to study the month of September (β_9). As described by Bouges et al. (2009) it will be considered the t test to compare the means and the F test to compare the variances.

In the next step, it is calculated the monthly returns with the GARCH(1,1) with t-student as error distribution with the purpose to study the returns of September with the extended dummy variables. The null hypothesis of the test the dummy variables is as defined:

$$H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = \beta_{12}$$

H_0 describes the expected returns for each month which have no significant impact as the expected return is equal to 0, if this hypothesis is rejected the returns have a significant impact. The goal will be to study the month of September (β_9).

After this step, to test the quality of the model, it is applied the ARCH effect test as described on Lundbergh & Teräsvirta (2002). It will reveal if the GARCH(1,1) model is robust and able to account all the volatility. All the calculations done do not consider transaction costs.

4. Empirical Results and Discussion

In order to discuss the empirical results, this chapter is divided into three groups of years. On each group, it is described by the empirical results of the tests done to understand if it stationary, if the results of the OLS model with HAC estimator and GARCH(1,1) with t-student as error distritbution are consistent, and also if we are able to capture the September effect, as described in the literature.

Table 2. Descriptive Statistics 1964-2016

	Mean	Median	Maximum	Minimum	Std. Dev	Skewness	Kurtosis	Jarque-bera	Probability
S&P 500	0.000246	0.000119	0.109572	-0.228997	0.010064	-1.026538	30.9224	451643.1	0***
Dow Jones	0.000001	0	0.25632	-0.096662	0.010025	1.091322	41.07347	837949.9	0***
N225	0.000198	0	0.132346	-0.161354	0.01232	-0.426994	13.3977	62710.83	0***

Table 3. Descriptive Statistics 1987-2016

	Mean	Median	Maximum	Minimum	Std. Dev	Skewness	Kurtosis	Jarque-bera	Probability
S&P500	0.000284	0.000274	0.10957	-0.22899	0.01145	-1.28614	31.78068	272296.1	0***
Dow Jones	-0.000300	-0.00028	0.25632	-0.10508	0.01113	1.72337	46.60217	623806.9	0***
N225	0.000002	0.00000	0.13234	-0.16135	0.01463	-0.29158	10.81714	20037.11	0***
DEUTSCHE BORSE DAX	0.000266	0.000462	0.10797	-0.13709	0.01423	-0.32549	9.188053	12624.57	0***
FTSE 100 HONG KONG	-0.000270	-0.000149	0.39723	-0.15146	-0.15146	0.01575	71.09844	1522481	0***
MICEX	-0.000226	-0.000310	0.10432	-0.09723	0.01046	0.75711	15.47228	51472.49	0***
NASDAQ	-0.000350	0.000705	0.12047	-0.13254	0.01405	0.23822	1097717	8082.132	0***
FTSE 100	-0.000185	-0.00012	0.13028	-0.09384	0.01109	0.48127	12.66678	30773.5	0***

Table 4. Descriptive Statistics 2004-2016

	Mean	**Median**	**Maximum**	**Minimum**	**Std. Dev**	**Skewness**	**Kurtosis**	**Jarque-bera**	**Probability**
S&P500	-0.000201	-0.000348	0.094695	-0.109572	0.012110	0.341406	14.69586	17900.91	0***
Dow Jones	-0.000194	-0.000331	0.082005	-0.105083	0.011156	0.097977	14.41125	16978.43	0***
N225	-0.000163	0	0.12111	-0.132346	0.015230	0.516744	11.41168	9367.096	0***
DEUTSCHE BORSE DAX	-0.000317	-0.000746	0.074335	-0.107975	0.013736	0.040550	9.229687	5062.198	0***
FTSE 100 HONG KONG	-0.000225	-0.000304	0.109957	-0.098655	0.013242	0.200414	10.69226	7737.816	0***
MICEX	-0.000173	-0.000564	0.104329	-0.097231	0.016140	0.663380	14.39146	17153.14	0***
EURONEXT LISBON	0.000153	-0.000093	0.103792	-0.101959	0.012750	0.246938	9.362522	5311.297	0***
NYSE	-0.000163	-0.000366	0.104594	-0.124942	0.012010	0.398690	15.78287	21393.22	0***
NASDAQ	-0.000289	-0.000521	0.095877	-0.111594	0.013009	0.258137	10.85526	8082.132	0***
FTSE 100/JSESA ALL SHARE	-0.000440	-0.000346	0.075807	-0.068340	0.012160	0.196016	6.896551	2000.174	0***
FTSE 100	-0.000126	-0.000117	0.092656	-0.093843	0.011742	0.148116	11.20598	8793.447	0***

4.1. The year group 1964-2016

Unit root test

Table 5. Results of the unit-root test to the daily returns variable for the years of 1964-2016.

	t-statistic	Prob.
S&P500	-84.85784	0.0001***
NIKKEI225	-118.7662	0.0001***
DOW JONES	-85.12592	0.0001***

The symbol * represents the significance level 10% (*), 5% (**) and 1% (***). Calculated using Eviews.

The unit root test of return variable performed as shown in Table 5 and it was found significant on all indexes, meaning the model is stationary, at a significance level of 1% for the year of 1964-2016. It means the shocks will not have an influence on the returns, which is ideal to study the seasonal anomalies.

ARCH LM test

Table 6.ARCH LM test to the ordinary least squares model for the years of 1964-2016.

	F-Test	Prob.
S&P500	279.4578	0***
NIKKEI225	608.1836	0***
DOW JONES	163.7617	0***

The symbol * represents the significance level 10% (*), 5% (**) and 1% (***). Calculated using Eviews.

For the years of 1964-2016, the Arch LM test performed as shown in Table 6 proved to be significant, for a significance level of 1% on all indexes. This confirms the presence of the ARCH effect in the OLS model.

The estimated expected return with the OLS model and the HAC estimator

Table 7. Estimated average daily return for September with the OLS model and the HAC estimator for the period of 1964-2016.

	β9	***Prob.***
S&P500	0.00074	0.06850*
NIKKEI225	-0.00181	0.03300**
DOW JONES	-0.00100	0.19820

The symbol * represents the significance level 10% (*), 5% (**) and 1% (***). Calculated using Eviews. More information on the annexes related to the other months.

For the calculated results in Table 7, for September the average return significance level was 5% for the index S&P 500 and 10% for the index NIKKEI225. The DOW JONES index was not found significant for September.

The F-Test

Table 8. The F-test results to compare the variances of the OLS model with HAC estimator for period of 1964-2016.

	F-Test
S&P500	0.49396
NIKKEI225	0.12028
DOW JONES	0.27860

The symbol * represents the significance level 10% (*), 5% (**) and 1% (***). Calculated using Eviews.

For the following test it was found not significant for all indexes, meaning the model is not able to correctly estimate the returns.

The estimated expected return with the GARCH(1,1) model

Table 9. Estimated average daily return for September with the GARCH(1,1) model with the error term t-student distribution for the period of 1964-2016. Calculated using Eviews.

	β9	***Prob.***
S&P500	0.00044	0.02370**
NIKKEI225	0.00038	0.08460*
DOW JONES	0.00016	0.45170

The symbol * represents the significance level 10% (*), 5% (**) and 1% (***). Calculated using Eviews. More information on the annexes related to the other months.

For the calculated results in Table 9, for September the average return significance level was 5% for the index S&P 500 and 10% for the index N225. The DJ index was not found significant for September.

ARCH test to the GARCH(1,1) model

Table 10. Results of the ARCH test to the GARCH(1,1) model for the period of 1964-2017.

	F-Test	***Prob.***
S&P500	7.142914	0.0075***
NIKKEI225	7.079642	0.0078***
DOW JONES	2.590672	0.1075

The symbol * represents the significance level 10% (*), 5% (**) and 1% (***). Calculated using Eviews.

As described on Table 10, the ARCH test to the GARCH(1,1) model was found significant at a level of 1% for S&P500 and N225, meaning the current model does not account all the volatility clustering. The Down Jon index was found not significant, suggesting the GARCH(1,1) is enough to capture all the volatility.

Accumulated returns for September

Table 11. Accumulated returns for September for the years of 1964-2016.

	$R_{September}$
S&P500	-15.09%**
NIKKEI225	-47.17%*
DOW JONES	10.041%

The symbol * represents the significance level 10% (*), 5% (**) and 1% (***). Calculated using Eviews.

In this group, there was no alignment with literature related to the average returns of September, as the returns of the month were positive in the GARCH (1,1) while the literature states that it is negative. These results cannot be considered the best ones as there is the presence of the ARCH effect. The DOW JONES is the only index where the model is enough to describe the volatility. In this group, it would not be possible to take advantage of the theory on any of the indexes for the month of September.

4.2. The year group 1987-2016

Unit root test

Table 12. Results of the unit-root test to the daily returns variable for the years of 1987-2016.

	t-statistic	***Prob.***
S&P500	-66.92359	0.0001***
NIKKEI225	-66.12674	0.0001***
DOW JONES	-67.21583	0.0001***
MICEX	-87.29327	0.0001***
DEUTSCHE BORSE DAX	-89.10348	0.0001***
FTSE 100	-41.40316	0.0001***
FTSE 100 HONG KONG	-48.18669	0.0001***
NASDAQ	-87.90176	0.0001***

The symbol * represents the significance level 10% (*), 5% (**) and 1% (***). Calculated using Eviews.

The unit root test of return variable performed as shown in Table 12 and it was found significant on all indexes, meaning the model is stationary, at a significance level of 1% for the year of 1987-2016. It means the shocks will not have an influence on the returns, which is ideal to study the seasonal anomalies.

ARCH LM test

Table 13. ARCH LM test to the ordinary least squares model for the years of 1987-2016.

	F-test	***Prob.***
S&P500	150.4924	0.0000***
NIKKEI225	287.946	0.0000***
DOW JONES	86.97898	0.0000***
MICEX	1040.443	0.0000***
DEUTSCHE BORSE DAX	283.7933	0.0000***
FTSE 100	1415.602	0.0000***
FTSE 100 HONG KONG	13.12889	0.0003***
NASDAQ	637.3097	0.0000***

The symbol * represents the significance level 10% (*), 5% (**) and 1% (***). Calculated using Eviews.

For the years of 1964-2016, the Arch LM test performed as shown in Table 13 proved to be significant, for a significance level of 1%, on all indexes. This confirms the presence of the ARCH effect in the OLS model.

The estimated expected return with the OLS model and the HAC estimator

Table 14. Estimated average daily return for September with OLS model and the HAC estimator for the period of 1987-2016

	β9	**Prob.**
S&P500	-0.00048	0.40000
NIKKEI225	-0.00076	0.30140
DOW JONES	0.00039	0.33080
MICEX	0.00120	0.03150**
DEUTSCHE BORSE DAX	-0.00126	0.14080
FTSE 100	0.00049	0.42900
FTSE 100 HONG KONG	-0.00052	0.69730
NASDAQ	0.00084	0.26170

The symbol * represents the significance level 10% (*), 5% (**) and 1% (***). Calculated using Eviews. More information on the annexes related to the other months.

For the calculated results in Table 14, for September the average return was found statistically significant at 5 % on MICEX, while the other indexes were not found statistically significant.

The F-Test

Table 15. The F-test results to compare the variances of the OLS model with HAC estimator for period of 1987-2016.

	F-Test
S&P500	0.69492
NIKKEI225	0.25327
DOW JONES	0.73567
MICEX	0.30106
DEUTSCHE BORSE DAX	0.02430**
FTSE 100	0.27993
FTSE 100 HONG KONG	0.97434
NASDAQ	0.31180

The symbol * represents the significance level 10% (*), 5% (**) and 1% (***). Calculated using Eviews.

It was found statistically significant at 5% in the DEUTSCHE BORSE DAX index, meaning that the model can account the variances in the model.

For the following test, it was found not significant for all the other indexes, meaning the model is not able to correctly estimate the returns.

The estimated expected return with the GARCH(1,1) model

Table 16. Estimated average daily return for September with the GARCH(1,1) model with the error term t-student distribution for the period of 1987-2016.

	β9	**Prob.**
S&P500	0.00035	0.21790
NIKKEI225	0.00013	0.18624
DOW JONES	-0.00028	0.33130
MICEX	0.00022	0.39820
DEUTSCHE BORSE DAX	0.00025	0.51900
FTSE 100	-0.00022	0.48390
FTSE 100 HONG KONG	-0.00075	0.05720*
NASDAQ	-0.00087	0.00730***

The symbol * represents the significance level 10% (*), 5% (**) and 1% (***). Calculated using Eviews. More information on the annexes related to the other months.

For the calculated results in Table 16, for September the average return significance level was 1% for the index NASDAQ and 10% for the index FTSE 100 HONG KONG. The other indexes were not found significant for September.

ARCH test to the GARCH(1,1) model

Table 17. ARCH-LM test is done to the GARCH(1,1) model for the years of 1987-2016.

	F-test	**Prob.**
S&P500	2.827472	0.0927*
NIKKEI225	6.541113	0.0106**
DOW JONES	0.506719	0.4766
MICEX	7.728799	0.0054***
DEUTSCHE BORSE DAX	0.098085	0.7541
FTSE 100	9.067791	0.0026***
FTSE 100 HONG KONG	1.221010	0.2692
NASDAQ	6.838708	0.0089***

The symbol * represents the significance level 10% (*), 5% (**) and 1% (***). Calculated using Eviews.

As described in Table 17, the ARCH test to the GARCH(1,1) model and it was found significant at 1% on MICA, FTSE and NASDAQ, 5% on N225 and 10% on S&P500. For these indexes, the GARCH(1,1) model is not able to account all the volatility clustering. Related to the N225, FTWIHKGL, GDAX and DJ, it was found not significant meaning that the GARCH(1,1) is enough to capture all the volatility.

Accumulated returns for September

Table 18. Estimated average daily return for September with OLS model and the HAC estimator for the period of 1987-2016.

	$R_{September}$
S&P500	-15.09%
NIKKEI225	-48.51%
DOW JONES	25.17%
MICEX	48.92%
DEUTSCHE BORSE DAX	-88.55%
FTSE 100	29.81%
FTSE 100 HONG KONG	-4.19%*
NASDAQ	8.09%***

The symbol * represents the significance level 10% (*), 5% (**) and 1% (***). Calculated using Eviews.

From 1987 to 2016, on the Table. 18 we can verify that it was found no alignment with the theory in all indexes, except FTSE 100 HONG KONG. The index FTSE 100 HONG KONG was estimated an average return with the GARCH (1,1) model that is significant and represents negative returns, as it is supposed. The NASDAQ index was found the presence of the ARCH effect on the GARCH (1,1) model. The other markets were not found significant. From these results, we can conclude that it was possible to take advantage of a short position in September for the index FTSE 100 HONG KONG.

4.3. The year group 2005-2016

Unit root test

Table 19. Results of the unit-root test to the daily returns variable for the years of 2005-2016.

	t-statistic	Prob.
S&P500	-43.93756	0.0000***
NIKKEI225	-57.82991	0.0001***
DOW JONES	-43.88745	0.0000***
MICEX	-26.98931	0.0000***
DEUTSCHE BORSE DAX	-55.72103	0.0001***
FTSE 100	-26.92835	0.0000***
FTSE 100 HONG KONG	-54.81218	0.0001***
NASDAQ	-56.06251	0.0001***
EURONEXT LISBON	-51.46794	0.0001***
FTSE 100/JSESA ALL SHARE	-55.04684	0.0001***
NYSE	-56.06251	0.0001***

The symbol * represents the significance level 10% (*), 5% (**) and 1% (***). Calculated using Eviews.

The unit root test of return variable performed as shown in Table 19 and it was found significant on all indexes, meaning the model is stationary, at a significance level of 1% for the year of 2005-2016. It means the shocks will not have an influence on the returns, which is ideal to study the seasonal anomalies.

ARCH LM test

Table 20. ARCH-LM test to the ordinary least squares model for the years of 2005-2016.

	F-test	**Prob.**
S&P500	154.3062	0***
NIKKEI 225	116.0833	0***
DOW JONES	137.688	0***
MICEX	470.2047	0***
DEUTSCHE BORSE DAX	92.94041	0***
FTSE 100	193.6473	0***
FTSE 100 HONG KONG	369.7052	0***
NASDAQ	184.525	0***
EURONEXT LISBON	108.2039	0***
FTSE 100/JSESA ALL SHARE	137.4416	0***
NYSE	210.7695	0***

The symbol * represents the significance level 10% (*), 5% (**) and 1% (***). Calculated using Eviews.

For the years of 2005-2016, the Arch LM test proved to be significant, for a significance level of 1% on all indexes. It means that there is a strong presence the ARCH effect on the ordinary least squares model.

The estimated expected return with the OLS model and the HAC estimator

Table 21. Estimated average daily return for September with the OLS model and the HAC estimator for the period of 2005-2016.

	β9	**Prob.**
S&P500	0.00079	0.35800
NIKKEI225	0.00041	0.72680
DOW JONES	-0.00106	0.17430
MICEX	0.00055	0.54740
DEUTSCHE BORSE DAX	-0.000247	0.50820
FTSE 100	-0.00032	0.72840
FTSE 100 HONG KONG	-0.00052	0.69730
NASDAQ	-0.00033	0.27950
EURONEXT LISBON	0.00041	0.72680
FTSE 100/JSESA ALL SHARE	-0.00014	0.88890
NYSE	0.00027	0.79850

The symbol * represents the significance level 10% (*), 5% (**) and 1% (***). Calculated using Eviews. More information on the annexes related to the other months.

From 2005 to 2016 with the OLS with HAC estimator model, it was found not significant for all markets the average return for September.

The F-Test

Table 22. The F-test results to compare the variances of the OLS model with HAC estimator for period of 2005-2016.

	F-Test
S&P500	0.876277
NIKKEI 225	0.686670
DOW JONES	0.765507
MICEX	0.573788
DEUTSCHE BORSE DAX	0.972533
FTSE 100	0.696419
FTSE 100 HONG KONG	0.824482
NASDAQ	0.265900
EURONEXT LISBON	0.904260
FTSE 100/JSESA ALL SHARE	0.788400
NYSE	0.969770

The symbol * represents the significance level 10% (*), 5% (**) and 1% (***). Calculated using Eviews.

For the following test it was found not significant for all indexes, meaning the model is not able to correctly estimate the returns.

The estimated expected return with the GARCH model

Table 23. Estimated average daily return for September with the GARCH(1,1) model with the error term t-student distribution for the period of 2005-2016.

	β9	**Prob.**
S&P500	-0.00074	0.09980*
NIKKEI 225	-0.00077	0.25620
DOW JONES	-0.00089	0.03280**
MICEX	-0.00040	0.40600
DEUTSCHE BORSE DAX	-0.00116	0.06250*
FTSE 100	-0.00051	0.27630
FTSE 100 HONG KONG	-0.00115	0.03640**
NASDAQ	-0.00109	0.05250*
EURONEXT LISBON	-0.00098	0.04870**
FTSE 100/JSESA ALL SHARE	-0.00101	0.07820*
NYSE	-0.00059	0.28080

The symbol * represents the significance level 10% (*), 5% (**) and 1% (***). Calculated using Eviews. More information on the annexes related to the other months.

From 2005 to 2016 with the GARCH(1,1) model, it was found not significant for all markets the average return for September.

ARCH LM test to the GARCH(1,1) Model

Table 24. ARCH LM test to the GARCH(1,1) model for the years of 2005-2016.

	F-test	**Prob.**
S&P500	1.833625	0.1758
NIKKEI 225	4.750227	0.0294**
DOW JONES	2.780346	0.0955*
MICEX	2.031463	0.1542
DEUTSCHE BORSE DAX	0.637805	0.4246
FTSE 100	0.541584	0.4618
FTSE 100 HONG KONG	1.255202	0.2626
NASDAQ	0.941185	0.3320
EURONEXT LISBON	0.884234	0.3471
FTSE 100/JSESA ALL SHARE	1.839597	0.1751
NYSE	4.338817	0.0373**

The symbol * represents the significance level 10% (*), 5% (**) and 1% (***). Calculated using Eviews.

The ARCH test to the GARCH(1,1) model for each index was found significant at 5% for NIKKEI225, NYSE and 10 % for the DOW JONES. The other indexes were not found significant.

Accumulated returns for September

Table 25. Accumulated returns for September for the years of 2005-2016.

	$R_{September}$
S&P500	2.53%
NIKKEI225	3.31%
DOW JONES	-7.07%
MICEX	15.86%
DEUTSCHE BORSE DAX	-6.37%
FTSE 100	4.62%
FTSE 100 HONG KONG	-0.73%
NASDAQ	-8.39%
EURONEXT LISBON	6.71%
FTSE 100/JSESA ALL SHARE	-4.38%
NYSE	8.49%

The symbol * represents the significance level 10% (*), 5% (**) and 1% (***). Calculated using Eviews.

The returns obtained for the period 2005-2016 it was aligned with the theory in the S&P500, DEUTSCHE BORSE DAX, FTWIHK, NASDAQ, EURONEXT LISBON and FTSE 100/JSESA ALL SHARE. The DOW JONES, NIKKEI225 and NYSE index it was found the ARCH effect. The other indexes were not aligned with the theory. From these results we can conclude that it would be possible to take advantage of the market in the indexes S&P500, DEUTSCHE BORSE DAX, FTWIHK, NASDAQ and FTSE 100/JSESA ALL SHARE where the investor would have a profit by taking a short position.

5. Conclusions

The main goal of the thesis was to study if the September Effect is captured in the indexes around the world and understand if it is possible to obtain a return taking advantage of it. The model used in this thesis to study if the monthly effect was present in September was the OLS with the HAC estimator and GARCH (1,1) model with the error term t-distribution. After analysing all the data, we can have mixed opinions related to the September effect existence in the different markets.

The OLS model was tested for stationarity and for the ARCH effect and it was found positive on both tests on all periods of time of each index. The presence of the ARCH effect leads to the necessity of using another model, which is aligned with theory.

The OLS with HAC estimator model did not allow us to take any conclusions on all markets except the DEUTSCHE BORSE DAX index. It was shown as a model which was significant, but the September effect was not captured. The results obtained might be related to the model that might not be the best one for this line of studies.

While using the GARCH(1,1) model it can be highlighted three scenarios. The first one is when the expected returns captured by the GARCH (1,1) model are negative, there is no ARCH effect to the GARCH (1,1) model, and the returns are negative. This happened in the years of 2005-2016 for the indexes S&P500, DEUTSCHE BORSE DAX, FTSE 100 HONG KONG, NASDAQ and FTSE 100/JSESA ALL SHARE, in the years of 1987-2016 for the index FTSE 100 HONG KONG. For this group, it is possible to say that is highly likely that for this period the September Effect is present, and it is highly likely to obtain an abnormal return.

It was found in some of the results a significance for the month of September, but the ARCH effect is present on the GARCH (1,1) model. In the results found significant was on 1964-2017 for S&P500 and NIKKEI225, on 1987-2016 for S&P500, NIKKEI225, MICEX, FTSE 100, NASDAQ and 2005-2016 for NIKKEI225, DOW JONES, NYSE.

Although our interest is to find evidence related to the presence of negative returns of the month of September, it is inconclusive as the model is not able to account all the volatility.

The rest of the results show that there is no significant data to support any evidence of the September effect as it is described in the literature.

The analysis of data also revealed something else. On the group where there was no ARCH effect the index DEUTSCHE BORSE DAX was significant for the period of 2005-2016, while in the other period which had longer time with data were not. This suggests that there might be an influence related to a temporary seasonal anomaly in the period of 2005-2016, while in the long run it might not exist.

For the period 1987-2016, while considering the GARCH(1,1) model as a criteria it would be possible for the investors to take advantage of the month of September for the index FTSE 100 HONG KONG with a short position. For the period 2005-2016 it would be possible to take advantage of the market in the indexes S&P500, DEUTSCHE BORSE DAX, FTWIHK, NASDAQ and FTSE 100/JSESA ALL SHARE where the investor would have a profit by taking a short position.

There are some limitations in this study as in most of the indexes calculated with the GARCH (1,1) model had the ARCH effect, meaning that the model used might not account for all the volatility.

The limitation of the number of observations might also cause an influence in not showing us the statistical relevance that might explain the accumulated negative return in financial markets.

It would be interesting to find in future research repetition of this study and remove the periods of the years with shocks in the financial markets, explore other models specifications which might be relevant for this type of research.

6. Bibliography

Agrawal, A., & Tandon, K., (1994), "Anomalies or Illusions - Evidence From Stock Markets in 18 Countries", *Journal of International Money and Finance*, *13*(1), 83–106.

Athambawa, J., (2015), "Calendar Effects of Colombo Stock Market", *Journal of Management*, *12*(2), 121–132.

Bachelier, L., (1900), "Theorie de La Speculation", *Annales Scientifiques de l'É.N.S. 3e Série*, *17*, 21–86.

Barone, E., (1990), "The italian stock market. Efficiency and calendar anomalies", *Journal of Banking and Finance*, *14*(2–3), 483–510.

Bollerslev, T., (1986), "Generalized autoregressive conditional heteroskedasticity", *Journal of Econometrics*, *31*(3), 307–327.

Bollerslev, T., (1987), "A Conditionally Heteroskedastic time series model for speculative prices and rates of return", *The Review of Economics and Statistics*, *69*(3), 542–547.

Bouges, J. C., Jain, R., & Puri, Y. R., (2009), "American depository receipts and calendar anomalies", *Applied Financial Economics*, *19*(1), 17–25.

Bouman, S., & Jacobsen, B., (2002), " The Halloween Indicator , ' Sell in May and Go Away ': Another Puzzle A",*American Economic Association*, *92*(5), Vol . 92 , No . 5 (Dec ., 2002), 1618–1635.

Brooks, C., & Burke, S. P., (2003), "Information criteria for GARCH model selection", *The European Journal of Finance*, *9*(6), 557–580.

Chou, J., Uma Rao, S. P., & Das, P. K., (2011), "The value premium and the CAPM", *Managerial Finance*, *37*(6), 517–536.

Connolly, R. A., (1989), "An Examination of the Robustness of the Weekend Effect", *The*

Journal of Financial and Quantitative Analysis, 133–169.

Connolly, R. A., (1991), "A posterior odds analysis of the weekend effect", *Journal of Econometrics*, *49*(1–2), 51–104.

Engle, R. F., (1982), "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation", *Econometrica*, *50*(4), 987.

Fama, E. F., (1970), "Efficient Capital Markets : A Review of Theory and Empirical Work", *The Journal of Finance*, *25*(2), 383–417.

French, K. R., (1980), "Stock returns and the weekend effect", *Journal of Financial Economics*, *8*(1), 55–69.

Gibson, S., Safieddine, A., & Titman, S., (2000), "Tax-Motivated Trading and Price Pressure: An Analysis of Mutual Fund Holdings", *The Journal of Financial and Quantitative Analysis*, *35*(3), 369–386.

Gregoriou, A., Kontonikas, A., & Tsitsianis, N., (2004), "Does the day of the week effect exist once transaction costs have been accounted for? Evidence from the UK", *Applied Financial Economics*, *14*(May), 215–220.

Gu, A. Y., & Simon, J. T., (2007), "The September Phenomenon of US Equity Market", In *Advances in Quantitative Analysis of Finance and Accounting Volume 5*, pp. 283–297.

Gultekin, M. N., & Gultekin, N. B., (1983), "Stock market seasonality. International Evidence", *Journal of Financial Economics*, *12*(4), 469–481.

Haug, M., & Hirschey, M., (2006), "January effect", *Financial Analysts Journal*, *62*(5), 78–88.

Haug, M., & Hirschey, M., (2006), "The September Swoon", 1–22.

Heston, S. L., & Sadka, R., (2006), "Seasonality in the cross-section of stock returns", *Journal of Financial Economics*.

Hirshleifer, D., & Shumway, T., (2003), "Good Day Sunshine : Stock Returns and the Weather", *Journal of Finance*, *58*(3), 1009–1032.

Imtiaz Mazumder, M., Chu, T. H., Miller, E. M., & Prather, L. J., (2008), "International day-of-the-week effects: An empirical examination of iShares", *International Review of Financial Analysis*, *17*(4), 699–715.

Kamstra, M. J., Kramer, L. A., & Levi, M. D., (2000), "Losing Sleep at the Market: The Daylight Saving Anomaly", *The American Economic Review*, *90*(4), 1005–1011.

Kamstra, Mark J., Lisa A. Kramer, and Maurice D. Levi, 2003, "Winter Blues: A SAD Stock Market Cycle", *American Economic Review*, vol. 93, 324-343..

Kramer, L. A., & Weber, J. M., (2011), "This is Your Portfolio on Winter: Seasonal Affective Disorder and Risk Aversion in Financial Decision Making", *Social Psychological and Personality Science*, *3*(2), 193–199.

Lundbergh, S., & Teräsvirta, T., (2002), "Evaluating GARCH models", *Journal of Econometrics*, *110*(2), 417–435.

Newey, W. K., & West, K. D., (1987), "A Simple , Positive Semi-Definite , Heteroskedasticity and Autocorrelation Consistent Covariance Matrix", *The Econometric Society*, *55*(3), 703–708.

Officer, R. R., (1975), "Seasonality in Australian Capital Markets", *Journal of Financial Economics*, *2*(1), 29–51.

Reinganum, M. R., (1983), "The anomalous stock market behavior of small firms in January", *Journal of Financial Economics*, *12*(1), 89–104.

Rystrom, D. S., & Benson, E. D., (1989), "Investor Psychology and the Day-of-the-Week Effect", *CFA Institute*, *45*(5), 75–78.

Schwert, G. W., (1990), "Stock Return and Real Activity a Century of Evidence.Pdf", *The*

Journal of Finance.

Shelby, K., & Frank, B., (2014), "The January Effect : A Test of Market Efficiency", *ASBBS Annual Conference: Las Vegas*, *21*(1), 423–434.

Siegel, J. J., (2014), "Stocks for the Long Run: The Definitive Guide to Financial Market Returns and Long-Term Investment Strategies", (Vol. 5th edition).

Tsay, R. S., (2010), "*Analysis of Financial Time Series* (Third Edit)", A John Wiley & sons INC, Publication

Zhang, J., Lai, Y., & Lin, J., (2017), "The day-of-the-Week effects of stock markets in different countries", *Finance Research Letters*, *20*, 47–62.

Annex I

Summary statistics for monthly return for the years of 1964-2016

Table 26. Dow Jones summary statistics for monthly return for the years of 1964-2016.

DOW JONES	Mean	Maximum	Minimum	Standard Deviation	Observations
Jan	-0.00066	0.07097	-0.04466	0.00963	1172
Feb	0.00003	0.03265	-0.04729	0.00864	1070
Mar	0.00002	0.06612	-0.04335	0.00969	1174
Apr	0.00006	0.04935	-0.05822	0.00903	1137
May	0.00016	0.03825	-0.04952	0.00873	1171
Jun	-0.00014	0.02723	-0.03447	0.00846	1137
Jul	0.00012	0.06155	-0.04751	0.00865	1174
Aug	-0.00029	0.03900	-0.06578	0.01014	1172
Sep	0.00009	0.04861	-0.07396	0.01038	1138
Oct	0.00041	0.25632	-0.09666	0.01529	1172
Nov	0.00034	0.06459	-0.05725	0.01056	1135
Dec	-0.00014	0.04113	-0.08014	0.00904	1176

Summary statistics for monthly return for the years of 1964-2016

Table 27. Nikkei225 summary statistics for monthly return for the years of 1964-2016

NIKKEI225	Mean	Maximum	Minimum	Standard Deviation	Observations
Jan	0.00059	0.07551	-0.05816	0.01237	1172
Feb	0.00030	0.06911	-0.05555	0.01074	1070
Mar	0.00066	0.07222	-0.11153	0.01296	1174
Apr	0.00045	0.07275	-0.09086	0.01238	1137
May	0.00006	0.04448	-0.07597	0.01059	1171
Jun	0.00011	0.05185	-0.08352	0.01169	1137
Jul	-0.00003	0.06079	-0.04093	0.01058	1174
Aug	-0.00041	0.06031	-0.07509	0.01269	1172
Sep	-0.00041	0.07426	-0.06864	0.01221	1138
Oct	-0.00011	0.13235	-0.16135	0.01640	1172
Nov	0.00040	0.07660	-0.07141	0.01271	1135
Dec	0.00077	0.05075	-0.06564	0.01128	1176

Summary statistics for monthly return for the years of 1964-2016

Table 28. S&P500 summary statistics for monthly return for the years of 1964-2016

S&P500	Mean	Maximum	Minimum	Standard Deviation	Observations
Jan	0.00037	0.04888	-0.07008	0.00970	1172
Feb	0.00002	0.03932	-0.05037	0.00868	1070
Mar	0.00051	0.06837	-0.04774	0.00960	1174
Apr	0.00067	0.04275	-0.06005	0.00909	1137
May	0.00007	0.04900	-0.03976	0.00882	1171
Jun	-0.00002	0.02907	-0.03658	0.00858	1137
Jul	0.00016	0.05573	-0.03910	0.00882	1174
Aug	-0.00008	0.04646	-0.07044	0.01033	1172
Sep	-0.00025	0.05279	-0.09200	0.01052	1138
Oct	0.00037	0.10957	-0.22900	0.01498	1172
Nov	0.00049	0.06692	-0.06948	0.01068	1135
Dec	0.00061	0.05008	-0.09354	0.00912	1176

Summary statistics for monthly return for the years of 1987-2016

Table 29. S&P500 summary statistics for monthly return for the years of 1987-2016.

S&P500	Mean	Maximum	Minimum	Standard Deviation	Observations
Jan	0.00024	0.04888	-0.07008	0.01095	663
Feb	0.00016	0.03932	-0.05037	0.00967	606
Mar	0.00059	0.06837	-0.04774	0.01095	665
Apr	0.00071	0.04275	-0.06005	0.01028	643
May	0.00046	0.04303	-0.03976	0.00945	663
Jun	-0.00011	0.02907	-0.03658	0.00936	644
Jul	0.00050	0.05573	-0.03910	0.00970	664
Aug	-0.00044	0.04632	-0.07044	0.01149	664
Sep	-0.00023	0.05279	-0.09200	0.01189	644
Oct	0.00024	0.10957	-0.22900	0.01827	663
Nov	0.00044	0.06692	-0.06948	0.01207	643
Dec	0.00082	0.05008	-0.09354	0.01013	665

Summary statistics for monthly return for the years of 1987-2016

Table 30. Dow jones summary statistics for monthly return for the years of 1987-2016

DOW JONES	Mean	Maximum	Minimum	Standard Deviation	Observations
Jan	-0.00017	0.07097	-0.04466	0.01057	663
Feb	-0.00031	0.04729	-0.03265	0.00930	606
Mar	-0.00056	0.04335	-0.06612	0.01085	665
Apr	-0.00098	0.05822	-0.04144	0.00978	643
May	-0.00037	0.03670	-0.03825	0.00891	663
Jun	0.00025	0.03447	-0.02723	0.00900	644
Jul	-0.00071	0.04751	-0.06155	0.00935	664
Aug	0.00055	0.06578	-0.03900	0.01097	664
Sep	0.00039	0.07396	-0.04861	0.01158	644
Oct	-0.00024	0.25632	-0.10508	0.01856	663
Nov	-0.00063	0.05725	-0.06459	0.01142	643
Dec	-0.00081	0.08014	-0.04113	0.00966	665

Summary statistics for monthly return for the years of 1987-2016

Table 31. Nikkei225 summary statistics for monthly return for the years of 1987-2016.

NIKKEI225	Mean	Maximum	Minimum	Standard Deviation	Observations
Jan	0.00001	0.07551	-0.05816	0.01501	663
Feb	0.00021	0.06911	-0.05555	0.01284	606
Mar	0.00037	0.07222	-0.11153	0.01573	665
Apr	0.00067	0.07275	-0.07234	0.01433	643
May	0.00005	0.04448	-0.07597	0.01236	663
Jun	-0.00043	0.04826	-0.08253	0.01337	644
Jul	0.00006	0.06079	-0.04093	0.01253	664
Aug	-0.00077	0.06031	-0.06135	0.01457	664
Sep	-0.00075	0.07426	-0.06864	0.01456	644
Oct	-0.00033	0.13235	-0.16135	0.01998	663
Nov	0.00037	0.07660	-0.07141	0.01540	643
Dec	0.00057	0.05075	-0.06564	0.01319	665

Summary statistics for monthly return for the years of 1987-2016

Table 32. MICEX summary statistics for monthly return for the years of 1987-2016.

MICEX	Mean	Maximum	Minimum	Standard Deviation	Observations
Jan	-0.00044	0.04658	-0.05081	0.01044	663
Feb	-0.00042	0.07746	-0.04817	0.00966	606
Mar	-0.00047	0.05731	-0.05511	0.00961	665
Apr	-0.00035	0.05840	-0.04528	0.00951	643
May	-0.00058	0.03786	-0.04040	0.00888	663
Jun	0.00017	0.04636	-0.03553	0.00874	644
Jul	-0.00051	0.03636	-0.04131	0.00867	664
Aug	0.00026	0.06858	-0.03761	0.00929	664
Sep	0.00076	0.07248	-0.06933	0.01069	644
Oct	-0.00001	0.09848	-0.09723	0.01629	663
Nov	-0.00025	0.09908	-0.06360	0.01127	643
Dec	-0.00085	0.10433	-0.05305	0.01009	665

Summary statistics for monthly return for the years of 1987-2016

Table 33. Deutsche Borse Dax summary statistics for monthly return for the years of 1987-2016.

DEUTSCHE BORSE DAX	Mean	Maximum	Minimum	Standard Deviation	Observations
Jan	-0.00011	0.07288	-0.07433	0.01445	663
Feb	0.00052	0.04559	-0.04875	0.01295	606
Mar	0.00050	0.06645	-0.06336	0.01402	665
Apr	0.00103	0.05895	-0.04159	0.01216	643
May	0.00033	0.05163	-0.04741	0.01132	663
Jun	0.00004	0.04240	-0.07067	0.01183	644
Jul	0.00077	0.07553	-0.05429	0.01283	664
Aug	-0.00108	0.06842	-0.09871	0.01499	664
Sep	-0.00138	0.06429	-0.08875	0.01575	644
Oct	0.00066	0.10797	-0.13710	0.02041	663
Nov	0.00079	0.09843	-0.07083	0.01481	643
Dec	0.00111	0.07355	-0.06062	0.01270	665

Summary statistics for monthly return for the years of 1987-2016

Table 34. FTSE 100 summary statistics for monthly return for the years of 1987-2016.

FTSE 100	Mean	Maximum	Minimum	Standard Deviation	Observations
Jan	-0.00002	0.05637	-0.04641	0.01028	663
Feb	-0.00045	0.03271	-0.03483	0.00985	606
Mar	-0.00006	0.05481	-0.05903	0.01088	665
Apr	-0.00087	0.03048	-0.05440	0.00907	643
May	-0.00007	0.03561	-0.05032	0.00950	663
Jun	0.00047	0.03197	-0.03515	0.00933	644
Jul	-0.00060	0.05589	-0.04877	0.01070	664
Aug	0.00023	0.04866	-0.03681	0.01105	664
Sep	0.00046	0.05885	-0.08470	0.01278	644
Oct	-0.00013	0.13029	-0.07938	0.01646	663
Nov	-0.00016	0.05871	-0.09384	0.01145	643
Dec	-0.00103	0.05329	-0.06007	0.00947	665

Summary statistics for monthly return for the years of 1987-2016

Table 35. FTSE 100 Hong Kong summary statistics for monthly return for the years of 1987-2016.

FTSE 100 HONG KONG	Mean	Maximum	Minimum	Standard Deviation	Observations
Jan	0.00016	0.10474	-0.08040	0.01679	663
Feb	-0.00129	0.06204	-0.14019	0.01419	606
Mar	0.00014	0.07647	-0.05594	0.01395	665
Apr	-0.00082	0.09097	-0.05460	0.01291	643
May	-0.00022	0.11255	-0.08540	0.01437	663
Jun	0.00020	0.26068	-0.07624	0.01655	644
Jul	-0.00123	0.05304	-0.04368	0.01144	664
Aug	0.00098	0.08776	-0.07629	0.01465	664
Sep	-0.00006	0.09495	-0.09200	0.01464	644
Oct	-0.00012	0.39723	-0.15147	0.02593	663
Nov	-0.00016	0.06528	-0.06618	0.01509	643
Dec	-0.00089	0.08661	-0.07408	0.01366	665

Summary statistics for monthly return for the years of 1987-2016

Table 36. NASDAQ summary statistics for monthly return for the years of 1987-2016.

NASDAQ	Mean	Maximum	Minimum	Standard Deviation	Observations
Jan	-0.00071	0.07506	-0.13255	0.01463	663
Feb	-0.00024	0.05125	-0.04075	0.01213	606
Mar	-0.00040	0.06511	-0.06827	0.01353	665
Apr	-0.00035	0.10168	-0.08545	0.01560	643
May	-0.00050	0.06118	-0.07637	0.01274	663
Jun	-0.00019	0.04202	-0.06246	0.01202	644
Jul	-0.00033	0.04777	-0.05633	0.01257	664
Aug	0.00016	0.08954	-0.05159	0.01356	664
Sep	0.00013	0.09588	-0.05848	0.01356	644
Oct	-0.00020	0.12048	-0.11159	0.01891	663
Nov	-0.00054	0.06752	-0.06300	0.01439	643
Dec	-0.00099	0.09381	-0.09964	0.01348	665

Summary statistics for monthly return for the years of 2005-2016

Table 37. S&P summary statistics for monthly return for the years of 2005-2016

S&P500	Mean	Maximum	Minimum	Standard Deviation	Observations
Jan	-0.00069	0.04257	-0.05426	0.01093	264
Feb	0.00019	0.03932	-0.05037	0.01045	243
Mar	0.00095	0.06837	-0.04774	0.01187	266
Apr	0.00094	0.03735	-0.04373	0.00921	257
May	-0.00002	0.04303	-0.03976	0.00971	265
Jun	-0.00062	0.02907	-0.03658	0.01060	258
Jul	0.00081	0.03085	-0.02958	0.00921	265
Aug	-0.00030	0.04632	-0.06896	0.01268	266
Sep	0.00010	0.05279	-0.09200	0.01351	258
Oct	0.00025	0.10957	-0.09470	0.01750	265
Nov	0.00025	0.06692	-0.06948	0.01522	257
Dec	0.00048	0.05008	-0.09354	0.01155	266

Summary statistics for monthly return for the years of 2005-2016

Table 38. Dow Jones summary statistics for monthly return for the years of 2005-2016

DOW JONES	Mean	Maximum	Minimum	Standard Deviation	Observations
Jan	0.00079	0.04093	-0.03450	0.00990	264
Feb	-0.00018	0.04729	-0.03265	0.00972	243
Mar	-0.00089	0.04335	-0.06612	0.01099	266
Apr	-0.00098	0.03627	-0.03142	0.00839	257
May	0.00020	0.03670	-0.03825	0.00889	265
Jun	0.00070	0.03447	-0.02723	0.00991	258
Jul	-0.00083	0.02661	-0.03025	0.00884	265
Aug	0.00039	0.05706	-0.03900	0.01163	266
Sep	-0.00027	0.07235	-0.04575	0.01208	258
Oct	-0.00033	0.08201	-0.10508	0.01646	265
Nov	-0.00047	0.05725	-0.06459	0.01391	257
Dec	-0.00046	0.08014	-0.04113	0.01038	266

Summary statistics for monthly return for the years of 2005-2016

Table 39. Nikkei225 summary statistics for monthly return for the years of 2005-2016.

NIKKEI225	Mean	Maximum	Minimum	Standard Deviation	Observations
Jan	0.00102	0.05816	-0.05710	0.01601	264
Feb	-0.00040	0.05555	-0.06911	0.01500	243
Mar	-0.00072	0.11153	-0.05522	0.01665	266
Apr	-0.00062	0.03876	-0.04310	0.01356	257
May	0.00028	0.07597	-0.04448	0.01327	265
Jun	0.00014	0.08253	-0.04826	0.01513	258
Jul	-0.00036	0.03374	-0.03907	0.01129	265
Aug	0.00083	0.05570	-0.03294	0.01388	266
Sep	0.00013	0.05080	-0.07426	0.01425	258
Oct	0.00033	0.12111	-0.13235	0.02234	265
Nov	-0.00094	0.07141	-0.06508	0.01597	257
Dec	-0.00168	0.06564	-0.05075	0.01265	266

Summary statistics for monthly return for the years of 2005-2016

Table 40. MICEX summary statistics for monthly return for the years of 2005-2016

MICEX	Mean	Maximum	Minimum	Standard Deviation	Observations
Jan	0.00006	0.04658	-0.04252	0.01129	264
Feb	-0.00074	0.04115	-0.03352	0.00975	243
Mar	-0.00056	0.05731	-0.05511	0.01053	266
Apr	-0.00060	0.03449	-0.02678	0.00835	257
May	-0.00029	0.03786	-0.04040	0.00970	265
Jun	0.00043	0.04636	-0.02609	0.01058	258
Jul	-0.00052	0.03260	-0.02543	0.00931	265
Aug	-0.00024	0.04043	-0.03761	0.01046	266
Sep	0.00061	0.07248	-0.06933	0.01250	258
Oct	0.00027	0.08844	-0.09723	0.01774	265
Nov	-0.00025	0.09908	-0.06360	0.01412	257
Dec	-0.00026	0.10433	-0.05305	0.01198	266

Summary statistics for monthly return for the years of 2005-2016

Table 41. DEUTSCHE BORSE DAX summary statistics for monthly return for the years of 2005-2016.

DEUTSCHE BORSE DAX	Mean	Maximum	Minimum	Standard Deviation	Observations
Jan	0.00055	0.07433	-0.05761	0.01352	264
Feb	-0.00021	0.04875	-0.03272	0.01232	243
Mar	-0.00095	0.05233	-0.05283	0.01326	266
Apr	-0.00106	0.04159	-0.05895	0.01245	257
May	-0.00038	0.03463	-0.05163	0.01193	265
Jun	0.00081	0.07067	-0.04240	0.01355	258
Jul	-0.00102	0.03886	-0.03141	0.01201	265
Aug	0.00100	0.05995	-0.04852	0.01421	266
Sep	-0.00025	0.05419	-0.05413	0.01442	258
Oct	-0.00066	0.07336	-0.10797	0.01840	265
Nov	-0.00074	0.07083	-0.09843	0.01526	257
Dec	-0.00091	0.06062	-0.07355	0.01212	266

Summary statistics for monthly return for the years of 2005-2016

Table 42. EURONEXT LISBON summary statistics for monthly return for the years of 2005-2016.

EURONEXT LISBON	Mean	Maximum	Minimum	Standard Deviation	Observations
Jan	-0.00015	0.06013	-0.03167	0.01264	264
Feb	-0.00044	0.05106	-0.03840	0.01171	243
Mar	-0.00069	0.03546	-0.03693	0.01066	266
Apr	-0.00021	0.05507	-0.04491	0.01198	257
May	0.00125	0.04359	-0.10196	0.01275	265
Jun	0.00168	0.07247	-0.03183	0.01348	258
Jul	0.00006	0.05461	-0.03903	0.01411	265
Aug	0.00006	0.05978	-0.04604	0.01266	266
Sep	0.00026	0.05357	-0.07723	0.01301	258
Oct	0.00014	0.10379	-0.09710	0.01687	265
Nov	0.00065	0.04190	-0.05887	0.01196	257
Dec	-0.00077	0.03872	-0.03684	0.00977	266

Summary statistics for monthly return for the years of 2005-2016

Table 43. FTSE 100 summary statistics for monthly return for the years of 2005-2016.

FTSE 100	Mean	Maximum	Minimum	Standard Deviation	Observations
Jan	0.00050	0.05637	-0.04641	0.01131	264
Feb	-0.00050	0.03271	-0.03483	0.01037	243
Mar	-0.00008	0.05481	-0.04764	0.01116	266
Apr	-0.00087	0.02647	-0.04192	0.00921	257
May	0.00030	0.03195	-0.05032	0.01051	265
Jun	0.00069	0.03197	-0.03515	0.01055	258
Jul	-0.00087	0.03197	-0.03032	0.01002	265
Aug	0.00020	0.04779	-0.03498	0.01200	266
Sep	0.00018	0.05446	-0.08470	0.01361	258
Oct	-0.00037	0.09266	-0.07938	0.01676	265
Nov	0.00023	0.05871	-0.09384	0.01325	257
Dec	-0.00094	0.05329	-0.06007	0.01010	266

Summary statistics for monthly return for the years of 2005-2016

Table 44. FTSE 100 Hong Kong summary statistics for monthly return for the years of 2005-2016.

FTSE 100 HONG KONG	Mean	Maximum	Minimum	Standard Deviation	Observations
Jan	0.00049	0.07156	-0.08040	0.01428	264
Feb	-0.00038	0.04574	-0.03276	0.01125	243
Mar	-0.00031	0.05042	-0.05594	0.01285	266
Apr	-0.00188	0.03028	-0.05442	0.01044	257
May	0.00041	0.03445	-0.05285	0.01066	265
Jun	0.00040	0.04012	-0.03695	0.01110	258
Jul	-0.00183	0.05304	-0.04368	0.01107	265
Aug	0.00112	0.05253	-0.05365	0.01303	266
Sep	-0.00003	0.04980	-0.06682	0.01354	258
Oct	-0.00066	0.10996	-0.09865	0.02059	265
Nov	0.00028	0.06528	-0.04334	0.01474	257
Dec	-0.00034	0.04851	-0.07408	0.01177	266

Summary statistics for monthly return for the years of 2005-2016

Table 45. NASDAQ summary statistics for monthly return for the years of 2005-2016.

NASDAQ	Mean	Maximum	Minimum	Standard Deviation	Observations
Jan	0.00076	0.05959	-0.04493	0.01275	264
Feb	-0.00033	0.04290	-0.03825	0.01117	243
Mar	-0.00105	0.04082	-0.06827	0.01287	266
Apr	-0.00078	0.03954	-0.03816	0.01094	257
May	-0.00027	0.04192	-0.04700	0.01092	265
Jun	0.00054	0.04202	-0.03017	0.01205	258
Jul	-0.00113	0.03163	-0.03450	0.01038	265
Aug	0.00012	0.07149	-0.05159	0.01373	266
Sep	-0.00033	0.09588	-0.05308	0.01379	258
Oct	-0.00041	0.08850	-0.11159	0.01770	265
Nov	-0.00011	0.06752	-0.06300	0.01546	257
Dec	-0.00047	0.09381	-0.05266	0.01247	266

Summary statistics for monthly return for the years of 2005-2016

Table 46. FJ203 summary statistics for monthly return for the years of 2005-2016.

FJ203	Mean	Maximum	Minimum	Standard Deviation	Observations
Jan	-0.00003	0.04721	-0.05149	0.01189	264
Feb	-0.00065	0.03338	-0.05119	0.01218	243
Mar	-0.00099	0.03915	-0.05601	0.01145	266
Apr	-0.00060	0.03531	-0.03139	0.00946	257
May	-0.00072	0.03777	-0.04233	0.01169	265
Jun	0.00055	0.06700	-0.04917	0.01299	258
Jul	-0.00079	0.03160	-0.04078	0.01061	265
Aug	-0.00017	0.04482	-0.03231	0.01238	266
Sep	-0.00017	0.05937	-0.05292	0.01316	258
Oct	-0.00088	0.07581	-0.06499	0.01453	265
Nov	-0.00008	0.05154	-0.06519	0.01316	257
Dec	-0.00072	0.04652	-0.06834	0.01183	266

Summary statistics for monthly return for the years of 2005-2016

Table 47. NYSE summary statistics for monthly return for the years of 2005-2016.

NYSE	Mean	Maximum	Minimum	Standard Deviation	Observations
Jan	0.00006	0.04829	-0.03291	0.01100	264
Feb	-0.00128	0.03815	-0.02634	0.00936	243
Mar	-0.00024	0.05529	-0.03893	0.01098	266
Apr	-0.00110	0.02821	-0.03377	0.00913	257
May	0.00002	0.03760	-0.04038	0.01027	265
Jun	0.00009	0.04560	-0.02859	0.01083	258
Jul	-0.00073	0.02514	-0.03233	0.00918	265
Aug	0.00053	0.06524	-0.05423	0.01131	266
Sep	0.00033	0.08577	-0.04273	0.01235	258
Oct	0.00027	0.07846	-0.12494	0.01894	265
Nov	0.00050	0.07350	-0.07757	0.01495	257
Dec	-0.00047	0.10459	-0.05284	0.01209	266

Annex II

Results about the daily average returns calculated with OLS and the probability for the years of 1964-2016

Table 48. Results about the daily average returns calculated with OLS and the probability for the years of 1964-2016 for the S&P500, DJ and N225.

1964-2016	S&P 500		DOW JONES		NIKKEI225	
	Returns	Prob.	Returns	Prob.	Returns	Prob.
c	0.00037	0.20540	-0.00066	0.02510	0.00059	0.10180
β2	0.00002	0.40560	0.00003	0.10370	0.00030	0.57970
β3	0.00051	0.73770	0.00002	0.10060	0.00066	0.88980
β4	0.00067	0.48350	0.00006	0.08560	0.00045	0.79250
β5	0.00007	0.46950	0.00016	0.04860	0.00006	0.29880
β6	-0.00002	0.34800	-0.00014	0.21730	0.00011	0.34770
β7	0.00016	0.61010	0.00012	0.05950	-0.00004	0.22030
β8	-0.00008	0.27500	-0.00030	0.38290	-0.00041	0.05060
β9	-0.00025	0.13810	0.00009	0.07450	-0.00041	0.05030
β10	0.00037	0.99960	0.00041	0.01000	-0.00011	0.16950
β11	0.00049	0.78150	0.00035	0.01660	0.00041	0.71970
β12	0.00061	0.55990	-0.00014	0.20850	0.00077	0.72310

Results about the daily average returns calculated with OLS and the probability for the years of 1987-2016

Table 49. Results about the daily average returns calculated with OLS and the probability for the years of 1987-2016 for S&P500 DJ and N225.

1987-2016	S&P 500		DOW JONES		NIKKEI 225	
	Returns	Prob.	Returns	Prob.	Returns	Prob.
c	0.00024	0.58860	-0.00017	0.70110	0.00001	0.98680
β2	0.00016	0.90360	-0.00031	0.81980	0.00021	0.81060
β3	0.00059	0.57570	-0.00056	0.52230	0.00037	0.65130
β4	0.00071	0.45550	-0.00098	0.18650	0.00067	0.41340
β5	0.00046	0.72230	-0.00037	0.73610	0.00005	0.96220
β6	-0.00011	0.58080	0.00025	0.50310	-0.00043	0.58920
β7	0.00050	0.68130	-0.00071	0.37550	0.00006	0.94720
β8	-0.00044	0.28050	0.00055	0.24270	-0.00077	0.33470
β9	-0.00024	0.45320	0.00039	0.36600	-0.00075	0.34650
β10	0.00024	0.99390	-0.00024	0.90300	-0.00033	0.67690
β11	0.00044	0.75090	-0.00063	0.45290	0.00037	0.65700
β12	0.00082	0.35190	-0.00081	0.29050	0.00057	0.48580

Results about the daily average returns calculated with OLS and the probability for the years of 1987-2016

Table 50. Results about the daily average returns calculated with OLS and the probability for the years of 1987-2016 for GDAX, MICEX, FTSE 100 Hong Kong, FTSE and Nasdaq.

1987-2016	GDAX		MICEX		FTSE 100 HONG KONG		FTSE		NASDAQ	
	Returns	Prob.	Returns	Prob.	Returns	Prob.	Returns	Prob.	Returns	Prob.
c	-0.00011	0.83810	-0.00044	0.28140	0.00050	0.54370	-0.00002	0.95830	-0.00072	0.19050
β2	0.00052	0.42670	-0.00042	0.97570	-0.00087	0.45870	-0.00045	0.49100	-0.00024	0.54690
β3	0.00050	0.43160	-0.00047	0.95920	-0.00080	0.48440	-0.00006	0.95690	-0.00040	0.68510
β4	0.00104	0.14510	-0.00035	0.87920	-0.00238	0.04060	-0.00087	0.16960	-0.00035	0.64100
β5	0.00033	0.56910	-0.00058	0.80000	-0.00008	0.94180	-0.00007	0.94050	-0.00050	0.78150
β6	0.00004	0.84440	0.00017	0.29480	-0.00009	0.93600	0.00047	0.42460	-0.00019	0.49930
β7	0.00077	0.25680	-0.00051	0.90390	-0.00233	0.04340	-0.00060	0.34450	-0.00033	0.61920
β8	-0.00109	0.21360	0.00026	0.22660	0.00063	0.58470	0.00023	0.68330	0.00017	0.25430
β9	-0.00138	0.10900	0.00076	0.03860	-0.00052	0.65170	0.00046	0.42900	0.00013	0.27980
β10	0.00066	0.32120	-0.00001	0.45570	-0.00116	0.31420	-0.00013	0.85900	-0.00020	0.50710
β11	0.00080	0.24910	-0.00025	0.75030	-0.00022	0.85300	-0.00016	0.82490	-0.00054	0.82610
β12	0.00111	0.11850	-0.00085	0.47320	-0.00084	0.46670	-0.00103	0.09860	-0.00099	0.72580

Results about the daily average returns calculated with OLS and the probability for the years of 2005-2016

Table 51. Results about the daily average returns calculated with OLS and the probability for the years of 2005-2016 for the S&P500, DJ, N225, GDAX and MICEX.

2005-2016	S&P 500		DOW JONES		NIKKEI225		GDAX		MICEX	
	Returns	Prob.	Returns	Prob.	Returns	Prob.	Returns	Prob.	Returns	Prob.
c	-0.00069	0.35430	0.00079	0.24990	-0.00015	0.84680	0.00056	0.51210	0.00006	0.93080
β2	0.00089	0.41150	-0.00097	0.33050	-0.00029	0.79590	-0.00076	0.53350	-0.00081	0.43500
β3	0.00164	0.11880	-0.00169	0.08230	-0.00054	0.62580	-0.00150	0.20810	-0.00063	0.53580
β4	0.00163	0.12530	-0.00177	0.07090	-0.00006	0.95930	-0.00161	0.18060	-0.00066	0.51770
β5	0.00068	0.52210	-0.00060	0.54000	0.00140	0.20640	-0.00093	0.43480	-0.00036	0.72420
β6	0.00007	0.94480	-0.00009	0.92970	0.00183	0.10150	0.00026	0.82990	0.00037	0.71910
β7	0.00150	0.15470	-0.00162	0.09580	0.00021	0.84740	-0.00157	0.18900	-0.00058	0.56400
β8	0.00039	0.71230	-0.00040	0.67820	0.00021	0.85040	0.00045	0.70740	-0.00030	0.76310
β9	0.00079	0.45710	-0.00106	0.27600	0.00041	0.71230	-0.00080	0.50530	0.00055	0.58720
β10	0.00095	0.36970	-0.00112	0.24790	0.00029	0.79070	-0.00122	0.30820	0.00021	0.83450
β11	0.00095	0.37350	-0.00126	0.19810	0.00080	0.47370	-0.00129	0.28260	-0.00031	0.76230
β12	0.00117	0.26790	-0.00125	0.19780	-0.00062	0.57900	-0.00146	0.22040	-0.00033	0.74680

Results about the daily average returns calculated with OLS and the probability for the years of 2005-2016

Table 52. Results about the daily average returns calculated with OLS and the probability for the years of 2005-2016 for PSI20, FTSE, NASDAQ, FJ203 and FTSE 100 Hong Kong.

2005-2016	PSI20		FTSE		NASDAQ		FJ203		FTSE 100 Hong Kong	
	Returns	Prob.	Returns	Prob.	Returns	Prob.	Returns	Prob.	Returns	Prob.
c	-0.00015	0.84680	0.00050	0.49210	0.00076	0.34320	0.00050	0.49210	0.00050	0.54370
β2	-0.00029	0.79590	-0.00099	0.34240	-0.00109	0.34770	-0.00099	0.34240	-0.00087	0.45870
β3	-0.00054	0.62580	-0.00057	0.57440	-0.00181	0.10950	-0.00057	0.57440	-0.00080	0.48440
β4	-0.00006	0.95930	-0.00137	0.18500	-0.00154	0.17870	-0.00137	0.18500	-0.00238	0.04060
β5	0.00140	0.20640	-0.00020	0.84510	-0.00103	0.36150	-0.00020	0.84510	-0.00008	0.94180
β6	0.00183	0.10150	0.00020	0.84860	-0.00022	0.84480	0.00020	0.84860	-0.00009	0.93600
β7	0.00021	0.84740	-0.00137	0.18160	-0.00189	0.09600	-0.00137	0.18160	-0.00233	0.04340
β8	0.00021	0.85040	-0.00030	0.77230	-0.00064	0.57160	-0.00030	0.77230	0.00063	0.58470
β9	0.00041	0.71230	-0.00032	0.75750	-0.00109	0.34140	-0.00032	0.75750	-0.00052	0.65170
β10	0.00029	0.79070	-0.00087	0.39460	-0.00117	0.30200	-0.00087	0.39460	-0.00116	0.31420
β11	0.00080	0.47370	-0.00027	0.79650	-0.00087	0.44370	-0.00027	0.79650	-0.00022	0.85300
β12	-0.00062	0.57900	-0.00144	0.15970	-0.00123	0.27610	-0.00144	0.15970	-0.00084	0.46670

Annex III

Results about the daily average returns calculated with OLS with HAC estimator and the probability for the years of 1964-2016

Table 53. Results about the daily average returns calculated with OLS with HAC estimator and the probability for the years of 1964-2016 for S&P500, DJ and N225.

1964-2016	S&P 500		DOW JONES		NIKKEI225	
	Returns	Prob.	Returns	Prob.	Returns	Prob.
c	-0.00066	0.02910	-0.00041	0.63640	0.00059	0.08740
β2	0.00069	0.08060	0.00017	0.88420	-0.00029	0.53990
β3	0.00068	0.09140	0.00115	0.43350	0.00007	0.88880
β4	0.00072	0.06930	0.00170	0.15530	-0.00014	0.78550
β5	0.00082	0.03300	0.00037	0.73650	-0.00053	0.26240
β6	0.00052	0.17750	0.00019	0.86310	-0.00048	0.29780
β7	0.00078	0.05150	-0.00014	0.91500	-0.00062	0.18110
β8	0.00036	0.40960	-0.00041	0.77680	-0.00100	0.05980
β9	0.00074	0.06850	-0.00181	0.19820	-0.00100	0.03300
β10	0.00107	0.04270	0.00257	0.06830	-0.00070	0.19310
β11	0.00100	0.01940	0.00173	0.12980	-0.00018	0.71340
β12	0.00052	0.17170	0.00139	0.20710	0.00018	0.69650

Results about the daily average returns calculated with OLS with HAC estimator and the probability for the years of 1987-2016

Table 54. Results about the daily average returns calculated with OLS with HAC estimator and the probability for the years of 1987-2016 for S&P500, DJ, N225, GDAX and MICEX.

1987-2016	S&P 500		DOW JONES		NIKKEI225		DEUTSCHE BORSE DAX		MICEX	
	Returns	Prob.	Returns	Prob.	Returns	Prob.	Returns	Prob.	Returns	Prob.
c	0.00024	0.56010	-0.00017	0.69190	0.00001	0.98620	-0.00011	0.83470	-0.00044	0.27150
β2	-0.00008	0.89050	-0.00031	0.79720	0.00020	0.78990	0.00064	0.40760	0.00002	0.97660
β3	0.00035	0.53270	-0.00056	0.49580	0.00036	0.64890	0.00061	0.39490	-0.00003	0.95770
β4	0.00047	0.36160	-0.00098	0.11580	0.00066	0.37090	0.00115	0.10440	0.00009	0.86750
β5	0.00022	0.66390	-0.00037	0.68820	0.00004	0.95820	0.00045	0.49900	-0.00015	0.77450
β6	-0.00035	0.50100	0.00025	0.43050	-0.00044	0.54580	0.00016	0.82300	0.00061	0.24820
β7	0.00026	0.64720	-0.00071	0.33040	0.00005	0.94230	0.00089	0.23460	-0.00007	0.89610
β8	-0.00068	0.24490	0.00055	0.21980	-0.00078	0.33170	-0.00097	0.21370	0.00070	0.19770
β9	-0.00048	0.40000	0.00039	0.33080	-0.00076	0.30140	-0.00126	0.14080	0.00120	0.03150
β10	0.00000	0.99500	-0.00024	0.92460	-0.00034	0.68830	0.00078	0.38650	0.00043	0.55820
β11	0.00020	0.73660	-0.00063	0.43160	0.00036	0.64420	0.00091	0.22100	0.00018	0.75580
β12	0.00058	0.25600	-0.00081	0.21130	0.00056	0.42830	0.00122	0.08840	-0.00041	0.44340

Results about the daily average returns calculated with OLS with HAC estimator and the probability for the years of 1987-2016

Table 55. Results about the daily average returns calculated with OLS with HAC estimator and the probability for the years of 1964-2016 for FTSE 100 Hong Kong, FTSE and NASDAQ.

1987-2016	FTSE 100 HONG KONG		FTSE		NASDAQ	
	Returns	Prob.	Returns	Prob.	Returns	Prob.
c	0.00050	0.59280	-0.00002	0.95720	-0.00072	0.18910
β2	-0.00087	0.42220	-0.00043	0.44560	0.00048	0.54360
β3	-0.00080	0.50850	-0.00003	0.95290	0.00031	0.66160
β4	-0.00238	0.03140	-0.00084	0.11290	0.00036	0.64210
β5	-0.00008	0.94320	-0.00005	0.93110	0.00021	0.75770
β6	-0.00009	0.93500	0.00049	0.36750	0.00053	0.46160
β7	-0.00233	0.03640	-0.00058	0.32880	0.00038	0.59410
β8	0.00063	0.61120	0.00025	0.66550	0.00088	0.25530
β9	-0.00052	0.69730	0.00049	0.42900	0.00084	0.26170
β10	-0.00116	0.43440	-0.00011	0.88930	0.00051	0.59630
β11	-0.00022	0.86470	-0.00014	0.81140	0.00017	0.83180
β12	-0.00084	0.45970	-0.00101	0.06440	-0.00027	0.70790

Results about the daily average returns calculated with OLS with HAC estimator and the probability for the years of 2005-2016

Table 56. Results about the daily average returns calculated with OLS with HAC estimator and the probability for the years of 2005-2016 S&P500, DJ, N225, GDAX and MICEX.

2005-2016	S&P 500		DOW JONES		NIKKEI225		DEUTSCHE BORSE DAX		MICEX	
	Returns	Prob.	Returns	Prob.	Returns	Prob.	Returns	Prob.	Returns	Prob.
c	-0.00069	0.27660	0.00079	0.18870	-0.00015	0.87780	0.00056	0.56140	0.00006	0.92430
β2	0.00089	0.34870	-0.00097	0.27600	-0.00029	0.82020	-0.00076	0.54900	-0.00081	0.38740
β3	0.00164	0.06300	-0.00169	0.04060	-0.00054	0.64260	-0.00150	0.20070	-0.00063	0.48380
β4	0.00163	0.03300	-0.00177	0.01460	-0.00006	0.96340	-0.00161	0.17290	-0.00066	0.41100
β5	0.00068	0.40020	-0.00060	0.42820	0.00140	0.25900	-0.00093	0.40900	-0.00036	0.68740
β6	0.00007	0.93030	-0.00009	0.91550	0.00183	0.14250	0.00026	0.82520	0.00037	0.67370
β7	0.00150	0.07430	-0.00162	0.04780	0.00021	0.86640	-0.00157	0.18810	-0.00058	0.49940
β8	0.00039	0.66210	-0.00040	0.62720	0.00021	0.86980	0.00045	0.73600	-0.00030	0.71720
β9	0.00079	0.35800	-0.00106	0.17430	0.00041	0.72680	-0.00080	0.50820	0.00055	0.54740
β10	0.00095	0.42330	-0.00112	0.31090	0.00029	0.83820	-0.00122	0.39190	0.00021	0.85600
β11	0.00095	0.37120	-0.00126	0.19720	0.00080	0.50590	-0.00129	0.31570	-0.00031	0.77830
β12	0.00117	0.12980	-0.00125	0.08670	-0.00062	0.59940	-0.00146	0.19860	-0.00033	0.72200

Results about the daily average returns calculated with OLS with HAC estimator and the probability for the years of 2005-2016

Table 57. Results about the daily average returns calculated with OLS with HAC estimator and the probability for the years of 2005-2016 for PSI20, FTSE, NASDAQ, FJ203 and FTSE 100 Hong Kong.

2005-2016	PSI20		FTSE		NASDAQ		FJ203		FTSE 100 Hong Kong	
	Returns	Prob.	Returns	Prob.	Returns	Prob.	Returns	Prob.	Returns	Prob.
c	-0.00015	0.87780	0.00050	0.47730	0.00076	0.30280	-0.00003	0.97220	0.00050	0.59280
β2	-0.00029	0.82020	-0.00099	0.31450	-0.00033	0.30730	-0.00062	0.54940	-0.00087	0.42220
β3	-0.00054	0.64260	-0.00057	0.52780	-0.00105	0.06470	-0.00096	0.35220	-0.00080	0.50850
β4	-0.00006	0.96340	-0.00137	0.10060	-0.00078	0.09310	-0.00058	0.52630	-0.00238	0.03140
β5	0.00140	0.25900	-0.00020	0.82220	-0.00027	0.27610	-0.00069	0.49310	-0.00008	0.94320
β6	0.00183	0.14250	0.00020	0.83090	0.00054	0.81990	0.00058	0.57850	-0.00009	0.93500
β7	0.00021	0.86640	-0.00137	0.13460	-0.00113	0.05260	-0.00077	0.44360	-0.00233	0.03640
β8	0.00021	0.86980	-0.00030	0.76320	0.00012	0.53340	-0.00015	0.88550	0.00063	0.61120
β9	0.00041	0.72680	-0.00032	0.72840	-0.00033	0.27950	-0.00014	0.88890	-0.00052	0.69730
β10	0.00029	0.83820	-0.00087	0.44780	-0.00041	0.36110	-0.00085	0.45810	-0.00116	0.43440
β11	0.00080	0.50590	-0.00027	0.78890	-0.00011	0.46440	-0.00005	0.96320	-0.00022	0.86470
β12	-0.00062	0.59940	-0.00144	0.10340	-0.00047	0.15770	-0.00069	0.49800	-0.00084	0.45970

Results about the daily average returns calculated with OLS with HAC estimator and the probability for the years of 2005-2016

Table 58. Results about the daily average returns calculated with OLS with HAC estimator and the probability for the years of 2005-2016 for NYSE.

2005-2016	NYSE	
	Returns	Prob.
c	0.00006	0.92860
β2	-0.00135	0.14690
β3	-0.00031	0.73900
β4	-0.00116	0.16560
β5	-0.00005	0.96070
β6	0.00002	0.98150
β7	-0.00080	0.38000
β8	0.00046	0.61240
β9	0.00027	0.79850
β10	0.00021	0.87660
β11	0.00043	0.69400
β12	-0.00053	0.55480

Annexes IV

Results about the daily average returns calculated with GARCH (1,1) with t-student error distribution and the probability for the years of 1964-2016

Table 59. Results about the daily average returns calculated with GARCH (1,1) with t-student error distribution and the probability for the years of 1964-2016 for S&P500, Dow Jones, Nikkei 225.

1964-2016	S&P500		DOW JONES		NIKKEI225	
	Returns	Prob	Returns	Prob	Returns	Prob
β1	0.00070	0.00020	-0.00042	0.02980	0.00096	0.00000
β2	0.00035	0.08200	0.00031	0.14320	0.00072	0.00110
β3	0.00054	0.00600	-0.00002	0.92080	0.00089	0.00000
β4	0.00084	0.00000	-0.00010	0.63390	0.00085	0.00050
β5	0.00022	0.25420	0.00024	0.25130	0.00050	0.02500
β6	0.00014	0.46540	0.00011	0.58620	0.00059	0.00670
β7	0.00051	0.01010	0.00006	0.76560	0.00018	0.42940
β8	0.00026	0.21300	-0.00013	0.55920	0.00036	0.11200
β9	0.00044	0.02370	0.00016	0.45170	0.00038	0.08460
β10	0.00047	0.01620	0.00016	0.45370	0.00029	0.21600
β11	0.00078	0.00020	0.00018	0.42190	0.00036	0.12070
β12	0.00055	0.00530	0.00000	0.98410	0.00095	0.00010

Results about the daily average returns calculated with GARCH (1,1) with t-student error distribution and the probability for the years of 1987-2016

Table 60. Results about the daily average returns calculated with GARCH (1,1) with t-student error distribution and the probability for the years of 1987-2016 for S&P500, Dow Jones, Nikkei 225.

1987-2016	S&P500		DOW JONES		NIKKEI225	
	Returns	Prob	Returns	Prob	Returns	Prob
β1	0.00076	0.00540	-0.00072	0.00930	-0.00050	0.04360
β2	0.00085	0.00490	-0.00080	0.00860	-0.00086	0.00240
β3	0.00058	0.04770	-0.00070	0.01680	-0.00054	0.03610
β4	0.00084	0.00420	-0.00108	0.00020	-0.00059	0.02620
β5	0.00077	0.00770	-0.00061	0.02920	-0.00066	0.01060
β6	0.00013	0.64000	0.00001	0.95910	-0.00018	0.46500
β7	0.00093	0.00110	-0.00091	0.00120	-0.00096	0.00020
β8	0.00023	0.44120	0.00001	0.97320	-0.00011	0.66630
β9	0.00035	0.21790	-0.00028	0.33130	0.00022	0.39820
β10	0.00072	0.01180	-0.00081	0.00470	-0.00095	0.00030
β11	0.00091	0.00410	-0.00104	0.00110	-0.00049	0.09670
β12	0.00072	0.00940	-0.00083	0.00300	-0.00103	0.00020

Results about the daily average returns calculated with GARCH (1,1) with t-student error distribution and the probability for the years of 1987-2016

Table 61. Results about the daily average returns calculated with GARCH (1,1) with t-student error distribution and the probability for the years of 1987-2016 for MICEX, DEUTSCHE BORSE FAX, FTSE 100, FTSE 100 Hong Kong and NASDAQ.

1987-2016	MICEX		DEUTSCHE BORSE DAX		FTSE 100		FTSE 100 HONG KONG		NASDAQ	
	Returns	Prob	Returns	Prob	Returns	Prob	Returns	Prob	Returns	Prob
β1	-0.00050	0.04360	0.00059	0.11350	-0.00041	0.16200	-0.00100	0.00790	-0.00129	0.00000
β2	-0.00086	0.00240	0.00133	0.00090	-0.00066	0.04200	-0.00125	0.00210	-0.00133	0.00030
β3	-0.00054	0.03610	0.00063	0.12660	-0.00017	0.57750	-0.00012	0.76940	-0.00081	0.01150
β4	-0.00059	0.02620	0.00074	0.06010	-0.00069	0.02690	-0.00090	0.02710	-0.00081	0.01260
β5	-0.00066	0.01060	0.00088	0.01620	-0.00043	0.16350	-0.00063	0.10410	-0.00135	0.00000
β6	-0.00018	0.46500	0.00023	0.52610	0.00011	0.69780	-0.00038	0.33680	-0.00039	0.20240
β7	-0.00096	0.00020	0.00118	0.00180	-0.00080	0.01210	-0.00155	0.00000	-0.00108	0.00080
β8	-0.00011	0.66630	0.00012	0.75250	-0.00044	0.17130	0.00015	0.67740	-0.00093	0.00560
β9	0.00022	0.39820	0.00025	0.51900	-0.00022	0.48390	-0.00075	0.05720	-0.00087	0.00730
β10	-0.00095	0.00030	0.00115	0.00380	-0.00064	0.04850	-0.00087	0.02750	-0.00077	0.01870
β11	-0.00049	0.09670	0.00111	0.00620	-0.00036	0.28230	-0.00085	0.03180	-0.00112	0.00280
β12	-0.00103	0.00020	0.00148	0.00030	-0.00111	0.00090	-0.00052	0.20080	-0.00096	0.00440

Results about the daily average returns calculated with GARCH (1,1) t-student error distribution and the probability for the years of 2005-2016

Table 62. Results about the daily average returns calculated with GARCH (1,1) with t-student error distribution and the probability for the years of 2005-2016 for S&P500, Dow Jones, Nikkei 225, MICEX and Deutsche Borse Dax.

2005-2016	S&P500		DOW JONES		NIKKEI225		MICEX		DEUTSCHE BORSE DAX	
	Returns	Prob	Returns	Prob	Returns	Prob	Returns	Prob	Returns	Prob
β1	-0.00058	0.16610	-0.00048	0.22940	-0.00012	0.84270	-0.00049	0.22770	-0.00029	0.58510
β2	-0.00121	0.01030	-0.00104	0.01590	-0.00189	0.00840	-0.00133	0.00520	-0.00151	0.01210
β3	-0.00078	0.07340	-0.00094	0.02580	-0.00127	0.06500	-0.00037	0.38240	-0.00108	0.08980
β4	-0.00111	0.00960	-0.00126	0.00230	-0.00018	0.79980	-0.00071	0.09640	-0.00118	0.04870
β5	-0.00055	0.18170	-0.00038	0.33540	-0.00062	0.36620	-0.00010	0.81180	-0.00142	0.01770
β6	-0.00012	0.78060	0.00012	0.77780	-0.00068	0.31180	-0.00057	0.19250	0.00041	0.48980
β7	-0.00103	0.02560	-0.00084	0.05670	-0.00052	0.43250	-0.00101	0.03550	-0.00137	0.03620
β8	-0.00018	0.69520	0.00012	0.77210	-0.00004	0.94500	-0.00063	0.19020	0.00008	0.90380
β9	-0.00074	0.09980	-0.00089	0.03280	-0.00077	0.25620	-0.00040	0.40600	-0.00116	0.06250
β10	-0.00081	0.07410	-0.00077	0.07720	-0.00075	0.27710	-0.00086	0.06110	-0.00129	0.03530
β11	-0.00097	0.04130	-0.00102	0.02600	-0.00112	0.11640	-0.00068	0.17530	-0.00121	0.03210
β12	-0.00055	0.18970	-0.00062	0.11740	-0.00187	0.00630	-0.00086	0.07710	-0.00139	0.02350

Results about the daily average returns calculated with GARCH (1,1) with t-student error distribution and the probability for the years of 2005-2016

Table 63. Results about the daily average returns calculated with GARCH (1,1) with t-student error distribution and the probability for the years of 2005-2016 for FTSE 100, FTSE 100 Hong Kong, Euronext Lisbon and FJ203.

2005-2016	FTSE 100		FTSE 100 HONG KONG		NASDAQ		EURONEXT LISBON		FJ203	
	Returns	Prob	Returns	Prob	Returns	Prob	Returns	Prob	Returns	Prob
β1	-0.00028	0.53440	-0.00076	0.15010	-0.00066	0.21080	-0.00122	0.01010	-0.00054	0.27310
β2	-0.00122	0.01400	-0.00087	0.12990	-0.00139	0.02220	-0.00101	0.06660	-0.00125	0.02810
β3	-0.00012	0.80080	-0.00033	0.53190	-0.00084	0.11950	-0.00045	0.41080	-0.00053	0.33480
β4	-0.00083	0.07180	-0.00150	0.00760	-0.00078	0.12860	-0.00010	0.85330	-0.00078	0.16050
β5	-0.00059	0.19800	0.00012	0.81480	-0.00099	0.06540	0.00083	0.10030	-0.00075	0.14660
β6	0.00029	0.53320	-0.00019	0.73280	-0.00010	0.85360	0.00056	0.28980	-0.00001	0.99100
β7	-0.00099	0.05290	-0.00217	0.00010	-0.00159	0.00610	-0.00086	0.15110	-0.00135	0.01960
β8	-0.00013	0.79230	0.00019	0.71130	-0.00066	0.23590	-0.00100	0.04180	-0.00038	0.48500
β9	-0.00051	0.27630	-0.00115	0.03640	-0.00109	0.05250	-0.00098	0.04870	-0.00101	0.07820
β10	-0.00081	0.09950	-0.00084	0.12900	-0.00099	0.07360	-0.00079	0.10200	-0.00149	0.01280
β11	-0.00001	0.98160	-0.00070	0.18750	-0.00129	0.03010	-0.00023	0.64990	-0.00026	0.62200
β12	-0.00117	0.02010	-0.00007	0.90660	-0.00046	0.38920	-0.00157	0.00170	-0.00120	0.05590

Results about the daily average returns calculated with GARCH (1,1) with t-student error distribution and the probability for the years of 2005-2016

Table 64. Results about the daily average returns calculated with GARCH (1,1) with t-student error distribution and the probability for the years of 2005-2016 for NYSE.

2005-2016	NYSE	
	Returns	Prob
β1	-0.00053	0.29820
β2	-0.00170	0.00250
β3	-0.00073	0.16060
β4	-0.00111	0.03240
β5	-0.00013	0.79260
β6	-0.00034	0.5225
β7	-0.00081	0.11410
β8	-0.00006	0.90910
β9	-0.00059	0.28080
β10	-0.00040	0.45780
β11	-0.00031	0.60210
β12	-0.00073	0.18560